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Research Article

Modulation Classification using Cyclostationary Features on Fading Channels

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Abstract: In this study Automatic Modulation Classification (AMC) which is based on cyclostationary property of the modulated signal are discussed and implemented for the purpose of classification. Modulation Classification (MC) is a technique used to make better the overall performance of cognitive radios. Recently Cognitive Radio (CR) plays a key role in the field of communication. CR also used in the development of different wireless application and the exploitation of civilian and military applications. In modulated signals there is cyclostationary property that can be used for the detection of modulation formats. The extraction of cyclostationary features, is used for classification of digital modulation schemes at different values of SNR's, the considered modulation formats are FSK [2-64], PSK [2-64], PAM [2-64] and QAM [2-64] and the channel models considered are AWGN and Rayleigh flat fading. When the receiver, receives the signal it extract the cyclostationary features i-e Spectral Coherence Function (SCF) and Cyclic Domain Profile (CDP) and then uses a multilayer perception which is also known as Feed Forward Back Propagation Neural Network (FFBPNN) for classification of the modulation formats. The performance of proposed algorithm in the form of confusion matrix shows the correct classification accuracy of the considered modulation format. The simulation result shows the performance of proposed algorithm and feature extraction at lower SNR's.

Keywords: Automatic Modulation Classification (AMCs), Cyclic Domain Profile (CDP), cyclostationary features, Cognitive Radio (CR), Feed Forward Back Propagation Neural Network (FFBPNN), Spectral Coherence Function (SCF)

INTRODUCTION

The Automatic Modulation Classification (AMC) is a phenomenon used to automatically decide the modulation format of the transmitted signal by accomplishing signal processing technique on the signal received. It is the intermediate stage between detection of signal and demodulation (Mitola, 2000). AMC has a significant role in military and civil applications. Automatic modulation classification of a signal is an essential and challenging task in cognitive radio system. With increasing the acceptance of software defined radios and cognitive radios, the AMC is going to become a significant technology for commercial application. For better spectrum utilization the Federal Communication Commission (FCC) published a report on cognitive radios (FCC, 2002). A cognitive radio originally has become an important feature in communication system. The Cognitive Radio must be capable of sensing the signal present in the desired spectrum and then automatically classify the signal for the purpose of effective usage of spectrum resources (Mitola and Maguire, 1999). These attain the effective spectrum usage by opportunistically searching and exploiting vacant frequency bands. The basic uses of Cognitive Radios (CR) are interoperability among radios with different waveforms, effective spectrum utilization and enhanced quality of service (Ramkumar, 2009).

Basically AMC is based on two techniques; likelihood based detection and feature based detection (Dobre *et al*., 2007). In likelihood based detection a likelihood ratio function is organized of the received signal, that will based on several hypothesis test and according to the likelihood ratio based approach the decision will be made against the pre-define threshold (Ghauri *et al*., 2014a). While in the feature based detection the AMC will extract the main features requisite for classification from the signal at receiver and find out the default modulation format of the input signal (Ghauri *et al*., 2013). The feature based AMC is divided into two sub parts: one is signal processing part that will extract features from the signal and classifier part that will discriminate the considered modulation formats (Ghauri *et al*., 2014b).

Cyclostationary features extraction is proposed in Qian and Canyan (2010) for classification of modulation

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formats (AM, DSB, FM, 2FSK, 4FSK, BPSK and QPSK). The cyclostaionary features are extracted from Spectral Correlation Function (SCF) and it is shown that extracted features values are distributed over a different range, making the extracted features appropriate for classification. An advanced AMC algorithm for Cognitive Radio (CR) based on two dimensional property of Spectral Correlation Function (SCF) and Principal Component Analysis (PCA) is used to minimize the size of original data but does not lose its own features, thus providing good classification performance for less number of considered modulation formats (Jang *et al*., 2011). In Castro *et al*. (2012) two front end techniques Cognitive radio System Source (CSS) and cyclostaionary are discussed for classification of modulation formats. The advantages of cyclostaionary features detection are immunity from noise and signal interference over radiometric approach. The mathematical functions used to characterize cyclostaionary signals are Cyclic Autocorrelation Function (CAF) and Spectral Correlation Density (SCD) or Cyclic Domain Profile (CDP). In Aparna and Jayasheela (2012) investigates the use and advantages of cyclostaionary feature detection for classification of different modulation formats. Cyclostaionary feature detection has the ability to differentiate noise from primary user signal and also it can detect the primary user's modulation format. The problem of modulation classification in terms of front end and back end is discussed in Freitas *et al*. (2012). In front end author discusses the Cyclostaionary Feature extraction approach (SCF) and (CDP) for (BPSK and QPSK) in combination with different back ends (classifier) Naïve Bayes, Decision tree, SVM classifier, ANN and K-nearest Neighbor (KNN). In Liu *et al*. (2012) authors address the reception of unsynchronized signal. When there is a uniform distribution variable delay the signal will be stationary instead of cyclostaionary, thus resulting in limiting the practical range of cyclic spectrum for signal identification. In Haniz *et al*. (2013) discusses the factors (cyclic frequency mismatch) that may affect the Spectral Correlation Density (SCD), making it difficult to extract the required information like symbol rate. The proposed technique in which (SCD) of both the actual received signal and square of that received signal is used for compensation.

In this study we explore the hidden cyclostationarity properties of modulated signal for the classification of the considered modulation format. The features extracted from the received signal are spectral coherence function and cyclic domain profile. These features after extraction are input to the classifier to classify the corresponding modulation format. The classifier is capable of classification of the modulation schemes including FSK, PSK, PAM and QAM up to the order (2-64) at SNR of 0dB. The classification process is divided in to four scenarios i.e., {FSK 2to64}, {PSK 2to64}, {PAM 2to64} and {QAM 2to64}. The channel models considered throughout the simulation are AWGN and Rayleigh flat fading channel. The simulation result shows that proposed classifier algorithm has high classification accuracy at low SNR. The performance metric for simulations is confusion matrix.

SYSTEM MODEL

In Fig. 1, the system model for modulation classification is shown. The transmitter chooses one of the four modulation formats for the transmission of randomly generated bits stream. The system model uses cyclostationary feature detection at the receiver end for the classification of considered modulation format under the effect of AWGN and Rayleigh Flat fading channel model. At the receiving end the extraction of spectral coherence function and cyclic domain profile which are input to the neural network for the classification of modulation format.

The generalized expression for signal received is given by Ghauri *et al*. (2013):

$$r(n) = s(n) + g(n) \tag{1}$$

where,

- $r(n)$ = Complex baseband envelop of received signal,
- $g(n)$ = The additive white guassian noise with zero mean and a variance of $\sigma_g{}^2$ and $s(n)$ is given by:

$$s(n) = Ae^{i(w_o nT+\theta_n)} \sum_{j=-\infty}^{j=\infty} s(l)\, h(n\tau - j\tau + \epsilon_T\, \tau) \tag{2}$$

where,

- $s(l)$ = Input symbol sequence which is drawn from set of M constellations of known symbols and it is not necessary that symbols are equi-probable
- A = Amplitude of signal
- w_o = Angular frequency offset constant
- τ = Symbol spacing
- θ_n = The phase jitter which varies from symbol to symbol
- $h(\ldots)$ = Channel effects
- ϵ_T = The timing jitter

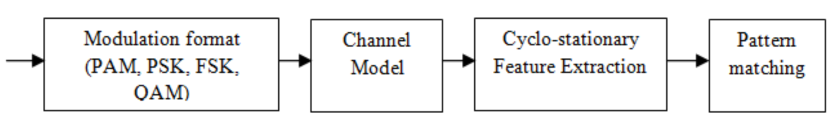

Fig. 1: System model

CYCLOSTATIONARY FEATURES EXTRACTION

The statistical properties of a signal that vary cyclically with time are known as cyclostationary process. As an example, maximum temperature of a particular city can be modeled as cyclostationary process. For the treatment of cyclostationary process, there are two different methods are normally used. One is probabilistic approach that is to view measurements as an instance of stochastic process. And the other is deterministic approach that is to view the measurements as a single time series from which the probability distribution is the event that occurs randomly over the time series (Gardner and Spooner, 1992).

Let s(t) be a sinusoidal wave with the frequency α and phase θ (Ramkumar, 2009):

$$s(t) = a\cos(2\pi\alpha t + \theta) \tag{3}$$

The Fourier coefficient of above signal is given as:

$$C_s^{\alpha} = \frac{1}{2}\alpha e^{j\theta} \tag{4}$$

Power spectral density (PSD) at range (-α to α) is defined as:

$$PSD(C_s(f)) = |C_s^{\alpha}|^2[\delta(f-\alpha) + \delta(f+\alpha)] \tag{5}$$

Here δ(f) shows impulse response. Now, consider a random noise signal:

$$s(t) = \cos(2\pi\alpha t + \theta) + n(t) \tag{6}$$

where, n(t) is the random noise. Autocorrelation of signal having a second order periodicity and frequency $\alpha \neq 0$ is given as (Yeung and Gardner, 1996):

$$\widehat{\gamma}_{s,s} = \lim_{T\to\infty} \frac{1}{T}\int_{-T/2}^{T/2} s\left(t+\frac{\tau}{2}\right) s\left(t-\frac{\tau}{2}\right) e^{-i2\pi\alpha t} dt \tag{7}$$

The process is called cyclostationary if its autocorrelation function is periodic over a time period T_0 (Ramkumar, 2009):

$$\gamma_s(t,\tau) = E\left\{s\left(t+\frac{\tau}{2}\right) s\left(t-\frac{\tau}{2}\right)\right\} \tag{8}$$

The Fourier coefficient of the above equation is known as cyclic autocorrelation:

$$\gamma_{s,s} = \lim_{T\to\infty} \frac{1}{T}\int_{-T/2}^{T/2} E\left\{s\left(t+\frac{\tau}{2}\right) s\left(t-\frac{\tau}{2}\right) e^{-i2\pi\alpha t}\right\} dt \tag{9}$$

According to Wiener Khintchine theorem if we take Fourier transform of an autocorrelation function it is equal to its PSD ($C_s(f)$):

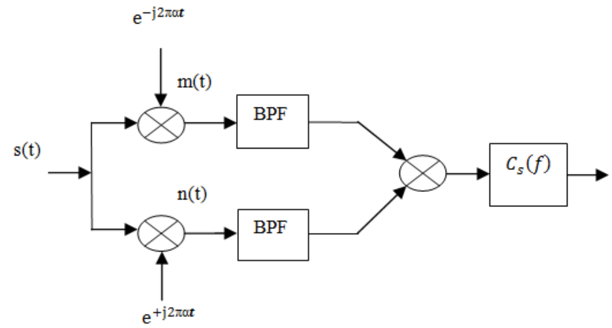

Fig. 2: Extraction of spectral coherence function through Band pass filter

$$C_s(f) = \int_{-\infty}^{\infty} \gamma_s(\tau) e^{-j2\pi f\tau} d\tau \tag{10}$$

Also, SCD (spectral coherence density) is the Fourier transform of cyclic autocorrelation function (Kim *et al*., 2007), given as:

$$C_s^{\alpha}(f) = \int_{-\infty}^{\infty} \gamma_{s,s}(\tau)\, e^{-i2\pi f\tau} d\tau \tag{11}$$

To determine the power in a frequency band first we imply the Fourier transform function on the incoming signal s(t). Here the m(t) and n(t) are the frequency translated signals. Then the desired signals m(t) and n(t) are passed through the band pass filter and then measure the correlation of the signal. The process is shown in Fig. 2.

The value of estimated SCD is described by the following equation (Kim *et al*., 2007):

$$C_s(f) = \lim_{B\to 0} \frac{1}{B}\langle |h_B^f(t) \otimes m(t)| |h_B^f(t) \otimes n(t)|^* \rangle \tag{12}$$

If a signal s (t) do not have frequency component at $f = \pm\frac{\alpha}{2}$ then covariance of two spectral component is equal to SCF (Fig. 3).

The normalized values after calculating the N-point FFT and are given as:

$$S_m(f) = S_s(f+\alpha/2) \text{ and } S_n(f) = S_s(f-\alpha/2) \tag{13}$$

The spectral coherence function is described as:

$$S_s^{\alpha}(f) = \frac{C_s^{\alpha}(f)}{[S_m(f)S_n(f)]^{\frac{1}{2}}} = \frac{C_s^{\alpha}(f)}{[S_m(f+\alpha/2)S_n(f-\alpha/2)]^{\frac{1}{2}}} \tag{14}$$

The automatic modulation classification based on cyclostationary investigates the detected signal Spectral Coherence (SC) for the classification of modulated signals. A large quantity of data is required for using SC; hence using the highest values of SC is the best solution. The highest values in spectral coherence are known as Cyclic Domain Profile that can be written as:

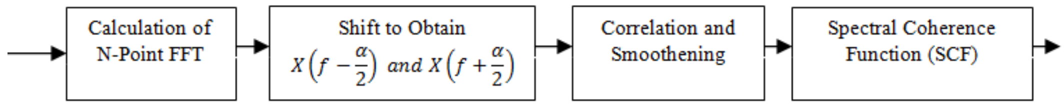

Fig. 3: Extraction of spectral coherence function

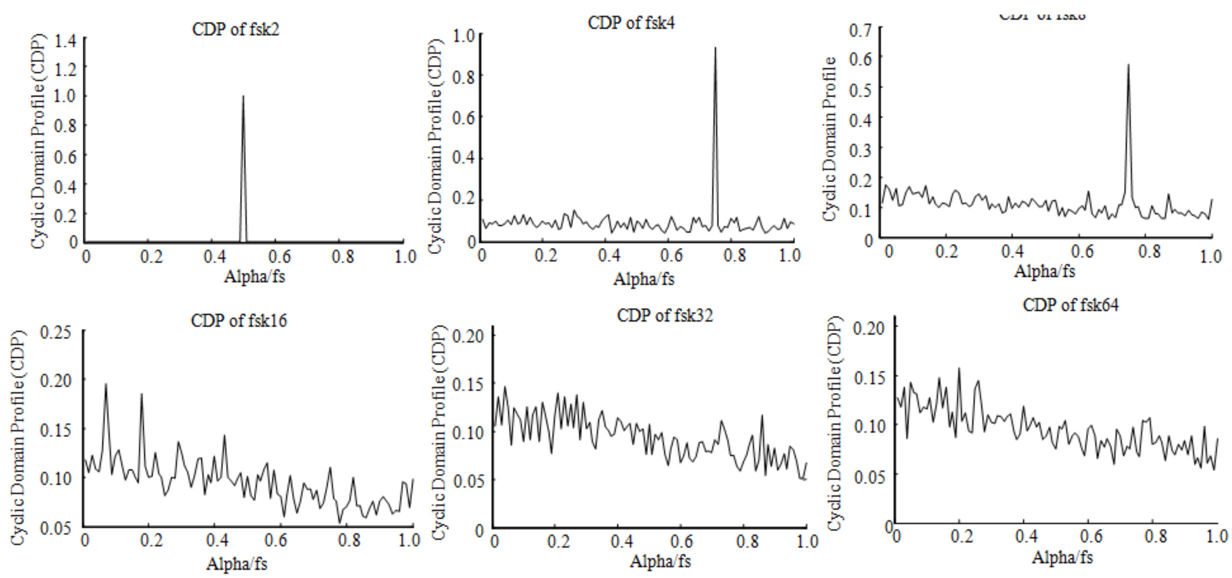

Fig. 4: Cyclic domain profile of frequency shift keying [2-64]

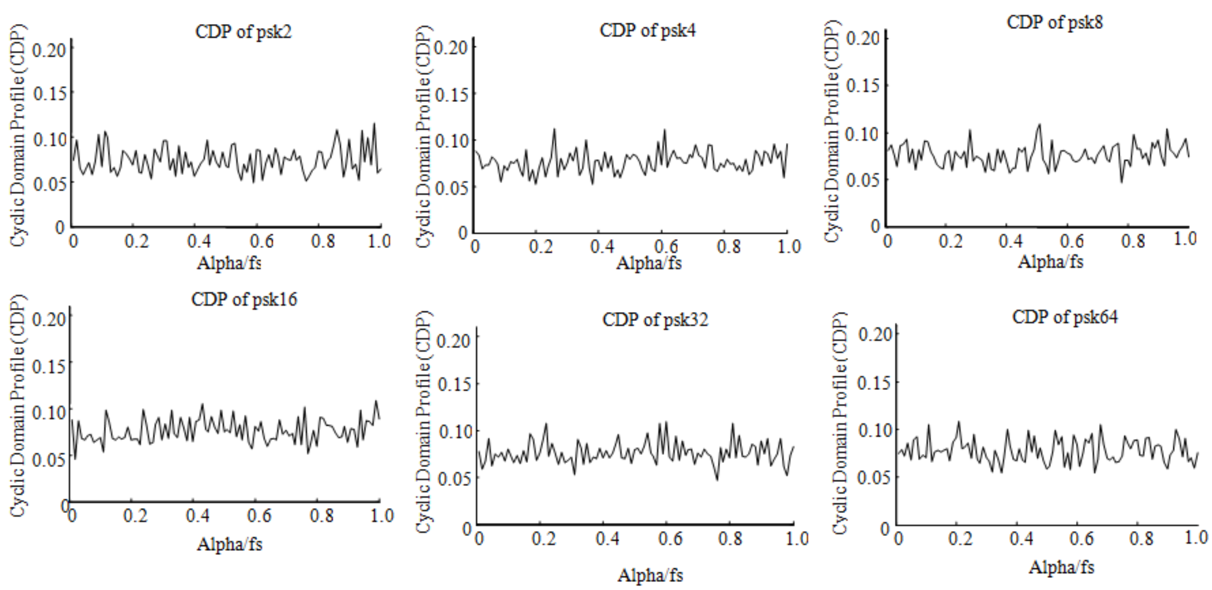

Fig. 5: Cyclic domain profile of pulse shift keying [2-64]

$$I(\alpha) = \max_f |S_s^{\alpha}(f)| \tag{15}$$

The Cyclic Domain Profile for FSK, PSK, PAM, QAM signals are used for SC function Generation.

In Fig. 4 it can be seen that Cyclic Domain Profile (CDP) for FSK has only one peak each at FSK2, FSK4 and FSK8 that resembles to symbol rate (F_{sym}). Due to this reason it is concluded that FSK2, FSK4 and FSK8 are the balanced modulation schemes i.e., these are balanced in Quadrature components and in phase.

Figure 5 shows the CDP for PSK (2-64). This figure shows that there are no sharp peaks, but many small peaks are shown. Due to these peaks it is not easy to decide the modulation format.

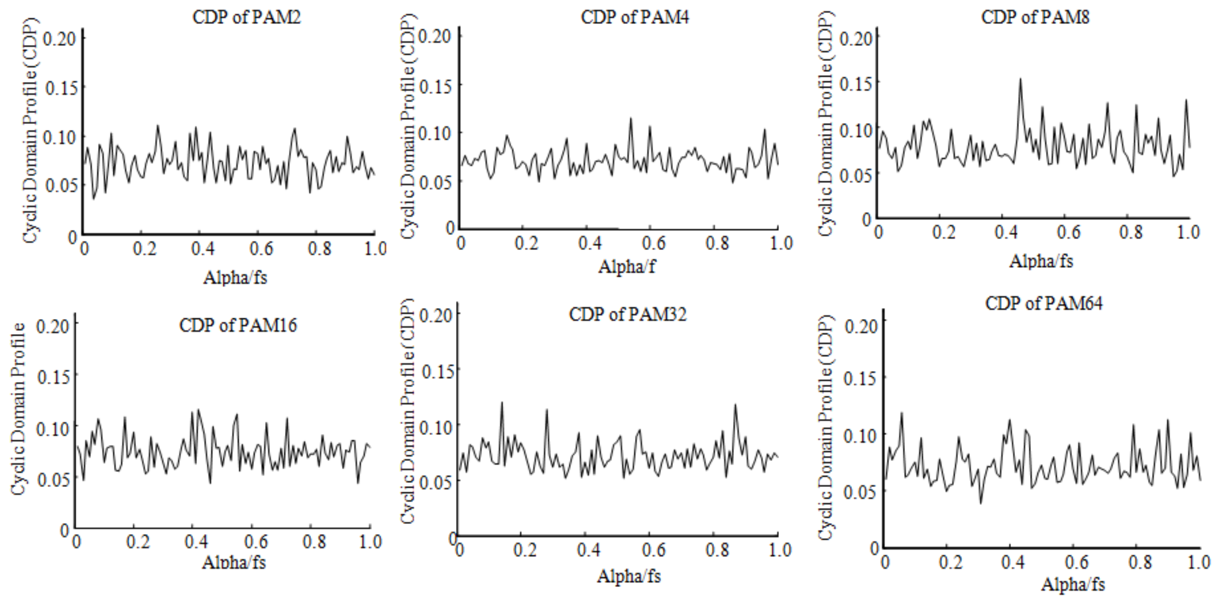

Fig. 6: Cyclic domain profile of pulse amplitude modulation [2-64]

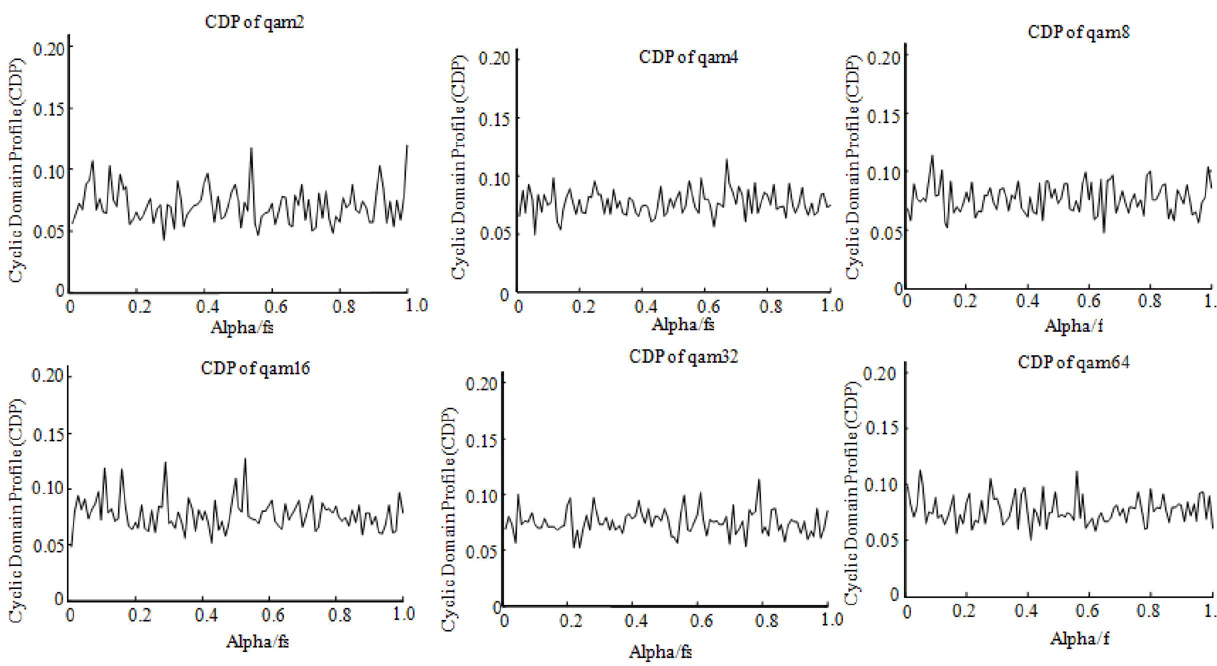

Fig. 7: Cyclic Domain profile of quadrature amplitude modulation [2-64]

Table 1: Parameters and their descriptions

S. No	Parameter	Description
1.	C_s^α	Fourier coefficient
2.	PSD	Power spectral density
3.	$\hat{\gamma}_{s,s}$	Autocorrelation
4.	$\gamma_{s,s}$	Cyclic autocorrelation
5.	$C_s(f)$	PSD
6.	SCD	Spectral coherence density
7.	$C_s^\alpha(f)$	SCD
8.	$S_s^\alpha(f)$	Spectral coherence function
9.	CDP	Cyclic domain profile
10.	$I(\alpha)$	CDP

Figure 6 shows the CDP for PAM 2-64. In this figure it is observed that there are several peaks as shown in PAM8, PAM32 and PAM64. In these peaks some corresponds to carrier frequencies (F_c) and some are related to symbol rate (F_{sym}) of the input signal.

Also in Fig. 7 the CDP's of QAM (2-64) are shown. This figure also shows that there are many distinct peaks as shown below. These peaks indicates the carrier frequencies (F_c) and some are related to symbol rate (F_{sym}) (Table 1).

PROPOSED ALGORITHM FOR MODULATION CLASSIFICATION

To classify the considered modulation formats, the proposed algorithm are divided in to two phases. In first phase, training of algorithm can be done by using the simplest delta rule. In delta rule errors are calculated and compared between the calculated outputs and the desired outputs. These errors are then used to adjust the weights. Feed Forward Back Propagation Algorithm (FFBPA) is very efficient and useful technique, used here to classify the desired modulation format.

Feed Forward back propagation algorithm (FFBPA): Feed Forward Back propagation algorithm use supervised learning. In FFBPA inputs propagates in forward direction, a sigmoid threshold is used the outputs for the product of inputs and its corresponding weights. Errors in the calculations are propagated in backward direction through the network and weights of the links are adjusted accordingly. The neural network learns from example that is what outputs you want from a particular set of inputs. The neural network is provided with example to learn and the weights are changed according to it so the neural network will produce required outputs once it is trained (Sharma *et al*., 2012). The input value and the corresponding output for that particular input are known as Training pair. In the training process ANN is initialized by assigning random values to all the links weights, e.g., between (-1, +1). After setting all the initial weights the inputs are applied to the ANN as shown in the Fig. 8. Inputs are applied at input neurons and output is calculated at the output neurons (Forward Pass). The outputs produced by ANN are completely different from our required outputs (Target). This is normal as the weights assigned to links were random. Than errors are calculated which is the difference between the produced outputs and our required outputs. These errors are than used to change the initial random weights of the links so that error will reduced (Reverse Pass). The same process is repeated until errors are minimized and the ANN produced our required outputs (Yeung and Gardner, 1996).

Training algorithm for ANN: The training of ANN is as follows:

Step 1: **Initialization of network:** In this step, weights are randomly assigned and inputs u(n) are applied to ANN and output y(n) of the network is produced.

Step 2: **Error calculation:** Error is calculated based upon the output y(n) of the ANN and the target value d(n) which is our desired response:

$$es(n) = [d(n) - y(n)](1 - y(n)) \tag{16}$$

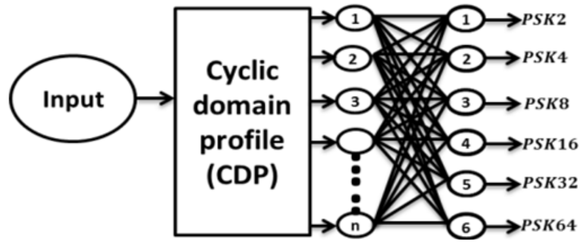

Fig. 8: Proposed algorithm for classification of PSK modulation formats

Table 2: Percentage of correct classification of proposed classifier

	Percentage of correct classification in case of FSK					
FSK	M = 2	M = 4	M = 8	M = 16	M = 32	M = 64
M = 2	100					
M = 4		100				
M = 8			100			
M = 16				99.9		
M = 32					100	
M = 64						99.2
	Percentage of correct classification in case of PSK					
PSK	M = 2	M = 4	M = 8	M = 16	M = 32	M = 64
M = 2	100					
M = 4		100				
M = 8			100			
M = 16				99.9		
M = 32					99.8	
M = 64						99.2
	Percentage of correct classification in case of PAM					
PAM	M = 2	M = 4	M = 8	M = 16	M = 32	M = 64
M = 2	100					
M = 4		100				
M = 8			99.9			
M = 16				99.3		
M = 32					99.4	
M = 64						99.2
	Percentage of correct classification in case of QAM					
QAM	M = 2	M = 4	M = 8	M = 16	M = 32	M = 64
M = 2	100					
M = 4		99.5				
M = 8			99.2			
M = 16				99.9		
M = 32					99.6	
M = 64						99.9

Due to sigmoid function term $(1 - y(n))$ is used; otherwise it is $(d(n) - y(n))$ for any threshold.

Step 3: **Updating of weights:** Using the error e(n) calculated in the step 2. The weight update equation is:

$$w(n) = w(n) - e(n) * y(n) \tag{17}$$

Step 4: **Updating of weights of Hidden layer:** Errors for the hidden layers cannot be calculated directly as there is no target values/output for the neurons of hidden layer. To determine the error of hidden layer neuron, there is back propagation of output of the neurons through weights:

$$e_h(n) = y_h(n)(1 - y_h(n))(\sum_{i=1}^{n} e_i(n) * w_i(n)) \quad (18)$$

Testing for ANN: The 40% of the normalized data are used to test the network. The performance of classifier is tested for different values of SNR.

SIMULATION RESULTS

The performance metric for the proposed classifier are confusion matrix. The considered modulation formats are FSK 2to64, PSK 2to64, PAM2to64 and QAM 2to64. The channel model considered throughout the simulation are AWGN and Rayleigh flat fading channel. The signal to noise ratio is fixed at 0 dB. The data matrix consists of input modulation format and target values are divided in to two portions; first portion which is 60% of data matrix for training the neural network and 40% of data matrix is for the testing purpose. The modulation formats considered in this research are divided in to four scenarios {FSK 2to64}, {PSK 2to64}, {PAM2to64} and {QAM 2to64}. For each scenario train set are 600x6 and test data set are 150x6. Table 2 shows the classification performance of proposed algorithm in case of {FSK 2 to 64}, {PSK 2to 64}, {PAM 2 to 64} and {QAM 2 to 64}.The classification accuracy for the case of FSK is 99.85%, PSK is 99.81%, PAM is 99.63% and for QAM is 99.68%. The proposed classifier classifies the modulation formats for considered scenario very well. The classification accuracy is approximately 100%.

AWGN channel: Now the modulated signal is passed through the Additive White Guassian Noise (AWGN) channel and performance of classifier is measured. All the results are calculated at SNR of 0dB. Selected the FFBPNN and train the network many times, till it leads to the desired performance where error approaches to zero. Training mode is completed, now test the network. Results are shown in the Table 3 for modulation format including PAM, PSK, FSK and QAM of order 2to64. Table 3, shows the percentage of correct classification in case of {FSK 2 to 64}, {PSK 2to 64}, {PAM 2 to 64} and {QAM 2 to 64} under the effect of additive white guassian noise at fixed SNR of 0dB. The classification accuracy for the case of FSK is 93.83%, PSK is 93.91%, PAM is 96.01% and for QAM is 96.31%. The classification performance is dropped down to 5% misclassification in case of additive white guassian noise.

Rayleigh flat fading channel: Table 4 shows the percentage of correct classification in case of {FSK 2 to 64}, {PSK 2to 64}, {PAM 2 to 64} and {QAM 2 to 64} under the effect of Rayleigh flat fading channel plus

Table 3: Percentage of correct classification on AWGN channel

	Percentage of correct classification in case of FSK on AWGN channel at 0dB SNR					
FSK	M = 2	M = 4	M = 8	M = 16	M = 32	M = 64
M = 2	93.7					
M = 4		94.2				
M = 8			93.1			
M = 16				90.1		
M = 32					96.2	
M = 64						95.7
	Percentage of correct classification in case of PSK on AWGN channel at 0dB SNR					
PSK	M = 2	M = 4	M = 8	M = 16	M = 32	M = 64
M = 2	95.6					
M = 4		97.7				
M = 8			93.4			
M = 16				94.5		
M = 32					92.1	
M = 64						90.2
	Percentage of correct classification in case of PAM on AWGN channel at 0dB SNR					
PAM	M = 2	M = 4	M = 8	M = 16	M = 32	M = 64
M = 2	95.6					
M = 4		98.0				
M = 8			97.9			
M = 16				97.8		
M = 32					94.3	
M = 64						92.5
	Percentage of correct classification in case of QAM on AWGN channel at 0dB SNR					
QAM	M = 2	M = 4	M = 8	M = 16	M = 32	M = 64
M = 2	95.8					
M = 4		92.3				
M = 8			99.9			
M = 16				95.3		
M = 32					96.4	
M = 64						98.2

Table 4: Percentage of correct classification on Rayleigh flat fading channel+AWGN

	Percentage of Correct Classification in case of FSK on Rayleigh Flat Fading channel at 0dB SNR					
FSK	M = 2	M = 4	M = 8	M = 16	M = 32	M = 64
M = 2	89.3					
M = 4		92.1				
M = 8			92.9			
M = 16				87.3		
M = 32					93.1	
M = 64						94.3
	Percentage of Correct Classification in case of FSK on Rayleigh Flat Fading channel at 0dB SNR					
PSK	M = 2	M = 4	M = 8	M = 16	M = 32	M = 64
M = 2	90.2					
M = 4		95.4				
M = 8			91.3			
M = 16				92.7		
M = 32					91.7	
M = 64						87.6
	Percentage of Correct Classification in case of FSK on Rayleigh Flat Fading channel at 0dB SNR					
PAM	M = 2	M = 4	M = 8	M = 16	M = 32	M = 64
M = 2	90.5					
M = 4		89.3				
M = 8			92.1			
M = 16				93.5		
M = 32					95.5	
M = 64						97.3
	Percentage of Correct Classification in case of FSK on Rayleigh Flat Fading channel at 0dB SNR					
QAM	M = 2	M = 4	M = 8	M = 16	M = 32	M = 64
M = 2	90.2					
M = 4		94.3				
M = 8			98.7			
M = 16				94.2		
M = 32					95.4	
M = 64						97.0

additive white guassian noise at fixed SNR of 0dB. The classification performance in case of FSK is 91.5%, in case of PSK is 91.48%, in case of PAM is 93.03 % and in case of QAM is 94.97 %. The overall classification performance in case of Rayleigh flat fading channel plus additive white guassian noise is 92.75%.

CONCLUSION

This study focus on development of feature based algorithm for classification of modulation formats (FSK, PSK, PAM and QAM) of order 2 up to 64 in AWGN and fading channel environment. The main focus of this study is cyclostationary based automatic modulation classification. The features extracted from the revived signal for considered modulation formats are spectral coherence function and cyclic domain profile. The extracted features are fed in to the classifier structure. The algorithm used for training of neural network is feed forward back propagation neural network. The classifier provides better performance at lower SNR. The performance of classifier can be increased by increasing the number of training session of FFBPNN. The classifier classifies approximately 100% the considered modulation scenarios in case of no channel effects and noise, in case of AWGN the classifier accuracy is 95% and in case of fading channel plus AWGN the classification accuracy is approximately 93%.

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