International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Mathematical Modelling of Engineering Problems
Vol. 8, No. 4, August, 2021, pp. 575-582
Journal homepage: http://iieta.org/journals/mmep

Optimized Polynomial Classifier for Classification of M-PSK Signals

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https://doi.org/10.18280/mmep.080410

Received: 29 March 2021
Accepted: 7 May 2021

Keywords:
automatic modulation classification, higher order cumulants, polynomial classifier, M-PSK, genetic algorithm

ABSTRACT

Automatic modulation classification (AMC) is the emerging research area for military and civil applications. In this paper, M-PSK signals are classified using the optimized polynomial classifier. The distinct features i.e., higher order cumulants (HOC's) are extracted from the noisy received signal and the dataset is generated with different number of samples, various SNR's and on several fading channels. The proposed classifier structure classifies the overall modulation classification problem into binary sub-classifications. In each sub-classification, the extracted features are expanded using polynomial expansion into higher dimension space. In higher dimension space numerous non-linearly separable classes becomes linearly separable. The performance of the proposed classifier is evaluated on Rayleigh and Rician fading channels in the presence of additive white gaussian noise (AWGN). The polynomial classifier performance is optimized using one of the famous heuristic computational techniques i.e., Genetic Algorithm (GA). The extensive simulations have been carried with and without optimization, which shows relatively better percentage classification accuracy (PCA) as compared with the state of art existing techniques.

1. INTRODUCTION

From past few decades, automatic modulation classification (AMC) application in communication systems has been an intriguing area for the researchers. AMC is a process to classify the modulation technique employed in the transmitted signals. AMC is conceded between the detection and demodulation of the received signal [1, 2]. AMC is generally divided into two categories:

1. Decision-Theoretic Approach (DTA)
2. Pattern Recognition Approach (PRA)

The decision-theoretic approach also termed as the likelihood-based approached in which the probability of correct decision is maximize via utilizing prior information. Even though the approach is optimal and high computational complexity. The decision theoretic approach provides optimal solution by calculating the likelihood function of the received signal. After having the likelihood function there are several tests to detect the modulation format such as: average likelihood ratio test (ALRT), generalized likelihood ratio test (GLRT), hybrid likelihood ratio test (HLRT), quasi-likelihood ratio test (Q-ALRT), kullback-leibler divergence test (KLDT) and the detailed explanation of decision theoretic approach can be found in [3-6].

In pattern recognition approach the received signals characteristics are exploited and various parameters are extracted. After extracting the parameters, feature selection is carried out. While comparing to the decision-theoretic approach, feature-based approach is sub-optimal, but with the advantage of reducing computational complexity [7]. The works [8-22] related to feature-based pattern recognition approach have been listed in Table 1. In the literature, authors have been utilized various classifier structures to classify the modulation formats [23, 24]. The classifiers are based on hidden Markov model (HMM), neural network based, support vector machine based, convolutional neural network based, recurrent neural network based, deep neural network based and Gabor filter network [25-28].

In this research, M-PSK signals are considered for classification using polynomial classifier. The polynomial classifier (PC) is optimized using one of the evolutionary computational techniques i.e., Genetic Algorithm. The PC transforms the feature space into higher dimension space (HDS). Various classes in low dimension space are non-linearly separable while in HDS it becomes linearly separable. The performance of PC is evaluated on various channel model and compared with the optimized PC (OPC).

The rest of the paper is organized as follows: In section 2 system model is presented with the extracted features and polynomial classifier structure. Proposed classifier algorithm and the optimization is discussed in Section 3. The detailed simulation is carried out in section 4. In the end, the paper is concluded.

2. SYSTEM MODEL

The system model for classification of M-PSK signals is shown in Figure 1. The signals have been considered for classification are PSK-4, PSK-8, PSK-16, PSK-32, and PSK-64. The modulated signal is transmitted over the faded channel (Rayleigh and Rician) with the addition of white gaussian noise. Higher order cumulants (HOCs) are selected as a feature set extracted from the received signal. In the first approach, these features are fed to the polynomial classifier, while in the second approach these features are optimized using Genetic Algorithm and fed to the polynomial classifier structure. The general expression of the received signal can be written as:

$$r_n = s_n + g_n \qquad (1)$$

where, r_n is the received signal, g_n is AWGN and s_n is the modulated signal.

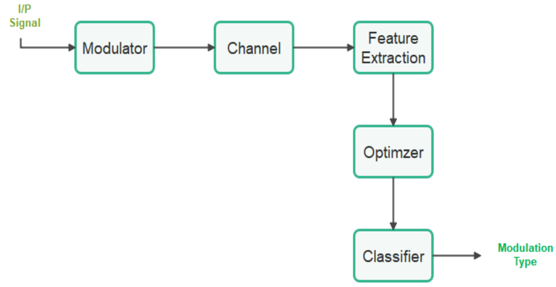

Figure 1. System model of the proposed algorithm

Table 1. Some existing feature-based techniques

Ref.	Classifier Algorithm	Modulation Formats	Channel	Features
[1]	Genetic Algorithm	QAM and PSK	AWGN	Spectral
[2]	Combined GP and KNN	BPSK, QPSK, QAM16, QAM64	AWGN	Cumulants
[8]	MAP	OFDM	AWGN, Fading	HOC
[9]	Pattern	M-PSK	Fading	HOC
[10]	ML	BPSK, QPSK, 8PSK, 16QAM	Rayleigh Fading, AWGN	High order cyclic cumulants
[11]	Hierarchical Classifier	M- ASK, FSK, PSK	AWGN	Instantaneous Spectral Feature
[12]	Linear and non-linear classifier	BPSK, 4PAM, QPSK, 16QAM, 64QAM	Multipath flat fading	HOC
[14]	Support Vector Machine	FSK, ASK, PSK	Fading	HOC
[15]	Pattern Recognition	M-PSK M-QAM	Flat Fading,	HOC
[16]	Artificial Neural Network	FSK, PSK, PAM, QAM	Rayleigh Flat Fading and AWGN	High Order Statistics, Spectral
[17]	Genetic Programming with KNN	BPSK, QPSK, 16QAM, 64QAM	AWGN	HOC
[18]	Artificial Neural Network	PSK, FSK, ASK, AM, FM, DSB	AWGN	Statistical, Spectral
[19]	Pattern Recognition (MLP)	M-PAM, M-PSK, M-FSK, M-QAM	AWGN, Rayleigh Flat Fading,	Cyclo-stationary
[20]	Pattern Recognition (MPL)	M-PAM, M-PSK, M-FSK, M-QAM	AWGN, Rayleigh Flat Fading, Rician Flat Fading	Spectral
[21]	Hierarchical Classifier	M-PSK	AWGN	HOC

2.1 Feature extraction

From the received signal as in Eq. (1), the higher order cumulants are extracted as features set. For this, the p^{th} order moment is defined as: -

$$M_{pq} = E[r^{p-q}(r^*)^q] \qquad (2)$$

The second order, forth order, sixth order cumulants and 8^{th} order cumulants expressions are expressed as follows [14]:

$$\mathrm{C}_{20} = \mathrm{M}_{20} = \mathrm{E}[\mathrm{r}^2(\mathrm{n})] \qquad (3)$$

$$\mathrm{C}_{21} = \mathrm{M}_{21} = \mathrm{E}[|\mathrm{r}(\mathrm{n})|^2] \qquad (4)$$

$$\mathrm{C}_{40} = \mathrm{M}_{40} - 3M_{20}^2 \qquad (5)$$

$$C_{41} = M_{40} - 3M_{20}M_{21} \qquad (6)$$

$$C_{42} = M_{42} - |M_{20}|^2 - 21M_{21} \qquad (7)$$

$$\mathrm{C}_{60} = \mathrm{M}_{60} - 15\mathrm{M}_{20}\mathrm{M}_{40} + 30{\mathrm{M}_{20}}^3 \qquad (8)$$

$$C_{61} = M_{61} - 15M_{21}M_{40} - 10M_{20}M_{41} + 30M_{20}^2M_{21} \qquad (9)$$

$$C_{62} = M_{62} - 6M_{20}M_{42} - 8M_{21}M_{41} - M_{22}M_{40} + 6M_{20}^2M_{22} + 24M_{21}^2M_{22} \qquad (10)$$

$$C_{63} = M_{62} - 9M_{21}M_{42} + 12M_{21}^3 - 3M_{20}M_{43} - 3M_{22}M_{41} + 18M_{20}M_{21}M_{22} \qquad (11)$$

$$C_{80} = M_{80} - 35M_{40}^2 - 28M_{60}M_{20} + 420M_{40}M_{20}^2 630M_{20}^4 \qquad (12)$$

From the Eqns. (3)-(12), the distinct features are extracted and higher order cumulants have been served as feature set. The features are extracted for different number of samples, different modulation formats, various SNR's and channel conditions i.e. Rician and Rayleigh.

2.2 Polynomial classifier

The crux of the polynomial classifier is to expand the original features set space into higher dimensional space, where various classes become linearly separable [20]. Generally, there are two stages of PC:

1) Training of PC
2) Testing of PC

2.2.1 Training stage of polynomial classifier

In the training stage, the received signal with known modulation type is used to find the weight vectors. The extracted features are transformed into higher dimensional space using polynomial expansion method to yield more distinct features. This expansion of the features vector allows us the linear separation of the modulation formats. The order of the classifier is same as the dimension of the expanded feature space. Higher order classifiers can be used, but for simplicity and due to ease of implementation generally lower order classifiers have been utilized, however, in this research, the second order polynomial classifier is used. In the second order polynomial classifier, the original extracted features plus the product of these features and squared values of these features have been found. Let C_i is the vector that contains input features which are higher order cumulants [21].

$$C_i = [C_{i,1}, C_{i,2}, C_{i,3}, \ldots C_{i,K}] \tag{13}$$

The feature vector C_i is expanded using polynomial expansion and the resulting expanded feature vector P_i is given below:

$$\begin{aligned} P_i = \big[C_{i,1}, C_{i,2}, C_{i,3}, \ldots, C_{i,K}, C_{i,1} \times C_{i,2}, \ldots, C_{i,1} \times, C_{i,2} \\ \times C_{i,3}, \ldots, C_{i,2} \times C_{i,K}, \ldots, C_{i,K-1} \\ \times\ C_{i,K}, C_{i,1}^2, C_{i,2}^2, \ldots, C_{i,K}^2\ \big]_{1\times R} \end{aligned} \tag{14}$$

The dimension of the expanded feature space is denoted by R, and K represents the total number of the features i.e., HOC. Expansion of features vectors for all N number of classes will result in a matrix G that is produced by concatenating all P_i. For N feature vectors, the expanded feature vectors are $P_1, P_2, \ldots, P_N$:-

$$P_N = [C_{N1}, C_{N2}, C_{N3}, \ldots, C_{NM}] \tag{15}$$

$$G = [P_1, P_2, \ldots, P_N] \tag{16}$$

$$X = G' \times G \tag{17}$$

In the next step, optimized weights are selected to reduce the minimum mean square error as: -

$$W = X^{-1} \times G \tag{18}$$

where, W is the weight vector. The weight is used in the testing stage to recognize the modulation type of the received signal. The block diagram of the training stage of polynomial classifier is shown in Figure 2.

Figure 2. Training stage

2.2.2 Testing stage of polynomial classifier

In the testing stage, the received signals that have unknown modulation formats are applied to the polynomial classifier to recognize the modulation formats of the received signals. The i^{th} feature vector C_i that contains higher order cumulants is extracted and then i^{th} expanded feature vector P_i is determined using the Eq. (14). The second order polynomial expansion is used, and expanded vector P_i is multiplied with the classifier weights W_i to obtain the scores S_i: -

$$S_i = P_i * W_i \tag{19}$$

These scores present the new super features for the polynomial classifier and based on these scores, the modulated signal, modulation format is determined. The class identity of vector C is determined by the following rule: -

$$\text{selected}\ \langle \text{class}_i \rangle = \arg\left(\max_i \{S_i\}\right) \tag{20}$$

For example, if there are two modulation types i.e., BPSK and QPSK, then there are two scores S_1 and S_2. If the score S_1 is greater than the S_2, then the modulation type is BPSK, otherwise the modulation type is QPSK. The block diagram shown in Figure 3, representing the training stage of polynomial classifier.

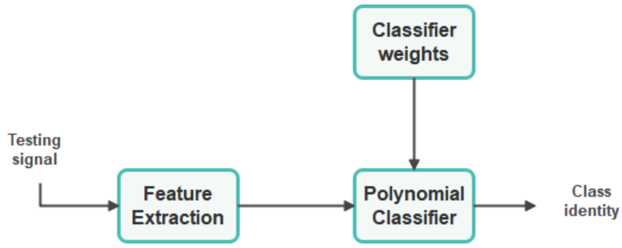

Figure 3. Testing stage

3. OPTIMIZATION OF POLYNOMIAL CLASSIFIER

Algorithm 1: **GA based polynomial classifier**

Inputs:
$N \rightarrow$ Number of samples
M $\rightarrow$ Modulation order
$U_b \rightarrow$ Upper bound of N
$L_b \rightarrow$ Lower bound of N
$s_n \rightarrow$ Modulated signal
$Ch_t \rightarrow$ Channel type (Rician or Rayleigh)
snr $\rightarrow$ Signal to noise ratio
Outputs:
return;
PCA $\rightarrow$ Percentage Classification Accuracy
Initialization:
Initialize;
$\forall$ *parameters*
$\forall$ *variables*

Main:

```
for i=1 to N
    ∀ M
   if Input_samples (i)= = (Ub, Lb)
            continue
      get s_n  =input samples(i)
   else
      break
   end if
end for
get Ch_t
apply snr
while rounds ≤ max round
    do
    rounds++
   features ← get
// Apply GA to optimize features
   while features ~ optimized
    do
     Apply GA
     generate dataset
```

```
      end while
  end while
  if training == true
     train polynomial classifier
  elseif testing == true
     test polynomial classifier
    evaluate PCA
  end if
```

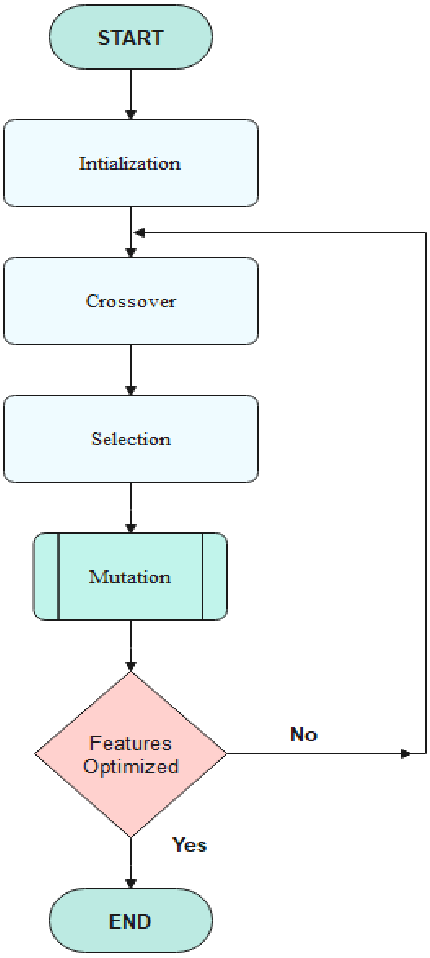

Figure 4. Flow chart of GA

To optimize the classifier performance, the GA is used to optimize the features and to reduce the mean square error by finding the optimized weight vector. The figure of merit of the classification problem is percentage PCA (PCA) which is enhanced by using optimal values of the overexcited parameters. GS is used as global optimization due to their greater efficiency and is stochastic optimization algorithm which adopts the survival of the fittest theory of Darwin. GA is used to take the optimal features and classifier must reject the similar features means redundant features to reduce the computational complexity. The flow chart of the genetic algorithm for classification of modulation formats is shown in Figure 4. The pseudo code of proposed classifier structure is shown.

4. SIMULATION RESULTS

The performance of polynomial classifier and optimized polynomial classifier have been evaluated for the classification of M-PSK signals. The figure of the merit of the considered problem is percentage classification accuracy (PCA). The simulation parameters are shown in the Table 2. The extensive simulations have been carried out with 512, 1024 and 2048 number of samples and different SNR's of 0dB, 5dB and 10dB. Two fading channel models have been considered throughout the simulations i.e., Rayleigh and Rician.

Table 2. Simulation parameters

Parameters	Values
Candidate Solutions	10-50
Cross-over	Single Point
Selection	Roulette Wheel
Mutation	Adaptive
Classifier	Polynomial
Iterations	1000
SNR in dB	0-10

4.1 Case-1: Classification on Non-Fading Channel Model

The classifier performance is evaluated on non-fading channel i.e., only considered the AWGN. Tables 3-11 shows the PCA for AWGN channel model with different number of samples and SNR's. From the Tables 3-5, the average PCA for the 512 number of samples is 87.5%, 89.46% and 91.94% at 0, 5 and 10 dB of SNR, respectively.

Table 3. PCA on AWGN Channel at SNR of 0dB, N=512

PSK	4	8	16	32	64
4	84.3%				
8		92.4%			
16			83.8%		
32				84.1%	
64					93%

Table 4. PCA on AWGN Channel at SNR of 5dB, N=512

PSK	4	8	16	32	64
4	87.3%				
8		93.5%			
16			86.4%		
32				87.1%	
64					93%

Table 5. PCA on AWGN Channel at SNR of 10dB, N=512

PSK	4	8	16	32	64
4	88%				
8		94.7%			
16			88.8%		
32				90.2%	
64					98%

Tables 6-8, the PCA improves as number of samples increases from 512 to 1024. The average PCA at 10dB of SNR is 93.9% which is better that 91.94% for 512 number of samples.

Table 6. PCA on AWGN Channel at SNR of 0dB, N=1024

PSK	4	8	16	32	64
4	87.3%				
8		93.4%			
16			90.8%		
32				85.1%	
64					98.1%

Table 7. PCA on AWGN Channel at SNR of 5dB, N=1024

PSK	4	8	16	32	64
4	88.3%				
8		94.4%			
16			91.1%		
32				89.4%	
64					98.5%

Table 8. PCA on AWGN Channel at SNR of 10dB, N=1024

PSK	4	8	16	32	64
4	89.1%				
8		95.2%			
16			93.8%		
32				92.22%	
64					99%

Table 9. PCA on AWGN Channel at SNR of 0dB, N=2048

PSK	4	8	16	32	64
4	88.9%				
8		95.1%			
16			92%		
32				89.2%	
64					99.45%

Table 10. PCA on AWGN Channel at SNR of 5dB, N=2048

PSK	4	8	16	32	64
4	89%				
8		97.2%			
16			93.8%		
32				92.1%	
64					100%

Table 11. PCA on AWGN Channel at SNR of 10dB, N=2048

PSK	4	8	16	32	64
4	92%				
8		98.7%			
16			94.8%		
32				96.2%	
64					100%

Tables 9-11 shows the percent accuracy of classification with 2048 number of samples and average PCA is quite improved as compared with 512 and 1024 number of samples i.e., 96.34%.

4.2 Case-2: Classification on Rician Fading Channel

The classifier performance is evaluated on Rician channel model. Tables 12-20 shows the PCA for Rician channel model with different number of samples and SNR's. From the Tables 12-14, the average PCA for the 512 number of samples is 86.4%, 88% and 88.26% at 0, 5 and 10 dB of SNR, respectively.

Tables 15-17, the PCA improves as number of samples increases from 512 to 1024. The average PCA at 10dB of SNR is 91.5% which is better that 88.26% for 512 number of samples. Table 18-20 shows the percent accuracy of classification with 2048 number of samples and average PCA is quite improved as compared with 512 and 1024 number of samples i.e., 94.1%.

Table 12. PCA on Rician Channel at SNR of 0dB, N=512

PSK	4	8	16	32	64
4	83%				
8		91.4%			
16			83.7%		
32				82.7%	
64					91%

Table 13. PCA on Rician Channel at SNR of 5dB, N=512

PSK	4	8	16	32	64
4	85.3%				
8		92.66%			
16			84.3%		
32				86%	
64					92%

Table 14. PCA on Rician Channel at SNR of 10dB, N=512

PSK	4	8	16	32	64
4	86.9%				
8		93.86%			
16			86.34%		
32				88.92%	
64					95%

Table 15. PCA on AWGN Channel at SNR of 0dB, N=1024

PSK	4	8	16	32	64
4	86.4%				
8		92%			
16			88.2%		
32				84.7%	
64					92%

Table 16. PCA on AWGN Channel at SNR of 5dB, N=1024

PSK	4	8	16	32	64
4	87.1%				
8		93.4%			
16			89.9%		
32				87%	
64					95.2%

Table 17. PCA on AWGN Channel at SNR of 10dB, N=1024

PSK	4	8	16	32	64
4	88.22%				
8		94%			
16			90%		
32				89.25%	
64					96 %

Table 18. PCA on Rician Channel at SNR of 0dB, N=2048

PSK	4	8	16	32	64
4	87%				
8		94.5%			
16			90.7%		
32				88%	
64					95%

Table 19. PCA on Rician Channel at SNR of 5dB, N=2048

PSK	4	8	16	32	64
4	88%				

8		95%			
16			91.1%		
32				89%	
64					97%

Table 20. PCA on Rician Channel at SNR of 10dB, N=2048

PSK	4	8	16	32	64
4	90%				
8		96.9%			
16			92.33%		
32				92%	
64					98.9%

4.3 Case-3: Classification on Rayleigh Fading Channel

The classifier performance is evaluated on Rayleigh channel model. Tables 21-29 shows the PCA for Rayleigh channel model with different number of samples and SNR's. The average PCA for 512, 1024 and 2048 number of samples at 10dB of SNR is 88.5%, 90.1% and 92.14%. The average PCA is slightly less at 5 dB and 0dB of SNR and can be seen from the tables 21-23, 24-26, 27-29.

Table 21. PCA on Rayleigh Channel at SNR of 0dB, N=512

PSK	4	8	16	32	64
4	81.98%				
8		90%			
16			81.7%		
32				82%	
64					90%

Table 22. PCA on Rayleigh Channel at SNR of 5dB, N=512

PSK	4	8	16	32	64
4	83.7%				
8		91.5%			
16			82.8%		
32				85.7%	
64					91.3%

Table 23. PCA on Rayleigh Channel at SNR of 10dB, N=512

PSK	4	8	16	32	64
4	84.8%				
8		92%			
16			84.3%		
32				87%	
64					94.5%

Table 24. PCA on Rayleigh Channel at SNR of 0dB, N=1024

PSK	4	8	16	32	64
4	85%				
8		91%			
16			86.9%		
32				83%	
64					91%

Table 25. PCA on Rayleigh Channel at SNR of 5dB, N=1024

PSK	4	8	16	32	64
4	85.56%				
8		92%			
16			87%		
32				85.6%	
64					93%

Table 26. PCA on Rayleigh Channel at SNR of 10dB, N=1024

PSK	4	8	16	32	64
4	86%				
8		93.6%			
16			88.96%		
32				87%	
64					95.1%

Table 27. PCA on Rayleigh Channel at SNR of 0dB, N=2048

PSK	4	8	16	32	64
4	85.5%				
8		93%			
16			88.9%		
32				85%	
64					91.8%

Table 28. PCA on Rayleigh Channel at SNR of 5dB, N=2048

PSK	4	8	16	32	64
4	86%				
8		94%			
16			90.6%		
32				87%	
64					95%

Table 29. PCA on Rayleigh Channel at SNR of 10dB, N=2048

PSK	4	8	16	32	64
4	88%				
8		95%			
16			91%		
32				90%	
64					96.7%

4.4 Case-4: Classification Performance Comparison

Table 30 shows the comparison of PCA of polynomial classifier and optimized polynomial classifier at 0dB of SNR. From the table, it is evident that after optimization, there is a significant improvement in PCA as compared without optimization. The PCA is 98% of OPC while 92.8% of PC for AWGN channel model at 2048 number of samples.

Table 30. PCA after Optimization Comparison at SNR of 0dB

	Samples	SNR in dB		
		0	5	10
AWGN	512	89.3%	91%	92.5%
	1024	93.6%	96%	97%
	2048	98%	99.1%	99.8%
Rician	512	88.8%	90.1%	91.9%
	1024	92%	93.5%	94.9%
	2048	95%	96.7%	98.9%
Rayleigh	512	87%	88.6%	91%
	1024	91.5%	95%	97.1%
	2048	93%	95%	97%

Table 31. Comparison of proposed algorithm with the existing techniques

Samples	SNR (dB)	Native	SVM	GP-KNN	Without optimization	With optimization
512	0	63%	64%	65%	87%	89%
	10	90%	91%	94%	91.9%	92.5%
1024	0	69%	70%	70%	90%	93.6%
	10	94%	94%	97%	93%	97%
2048	0	76%	75%	95%	92%	98%
	10	97%	97%	98%	96%	99.9%

In Table 31, the performance of proposed optimized polynomial classifier is compared with the well-known existing techniques and from the table, proposed OPC performs better in terms of percentage classification accuracy. The PCA is evaluated for different number of samples as well as different SNR's. The PCA is around 98% even at lower SNR's.

5. CONCLUSION

In this paper, an optimized polynomial classifier is employed to classify M-PSK signals. From the noisy received signal, HOCs are extracted and these feature vectors are fed into the polynomial classifier. The polynomial classifier expands the feature vector into a higher dimensional space in which various classes becomes linearly separable. The performance of the classifier is analyzed on Rician and Rayleigh fading channels in addition to white gaussian noise. The performance of classifier is also optimized using a Genetic Algorithm in conjunction with a polynomial classifier. From the extensive simulations, it is shown the supremacy of the proposed classifier as compared with the state of art existing techniques.

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