5
Modulation classification through k-medoids clustering

5.1 INTRODUCTION

In chapter 4, two clustering algorithms, OPTICS and k-means clustering were used. The modulation order was estimated using a density-based OPTICS clustering algorithm. The modulation domain was estimated using linear regression and partition-based k-means clustering. The algorithm in this chapter uses one clustering algorithm instead of two as used in the previous algorithm. k-means clustering is sensitive to outliers. Calculating centroid values in each iteration takes an average of the data points from the same cluster. An outlier can shift this new centroid; hence k-medoids clustering, a different form of the k-means clustering is used in the new algorithm. The main difference between the two algorithms lies in the calculation of the new centroid value. In k-medoid clustering, a new representative of a cluster will be from the data point. The block diagram for the algorithm is shown in Figure 5.1. In this algorithm, PSK and QAM are considered. For identification of the modulation scheme between QAM and PSK of different orders, blindly k medoids are estimated for k equals to 4, 8, 16, 64, and similarity to the ideal constellation structure is calculated. The final decision for the modulation schemes is given in favor of which similarity with the ideal structure is maximum.

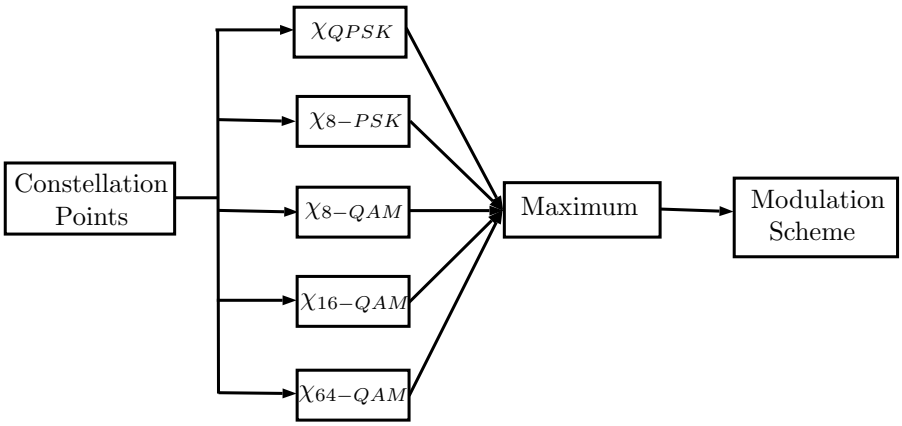


Figure 5.1 : Algorithm for classification using k-medoids

5.2 CLASSIFICATION USING K MEDOIDS AND SIMILARITY SCORE

5.2.1 k medoids clustering algorithm

It is a partition-based clustering algorithm and is slightly different from k-means clustering. It tries to minimize the squared error, and out of all data points, choose k points as centroids which makes it more robust to noise than $k-means$.

The algorithm steps are as follows:

Step1 : Randomly k data points out of N total points are chosen as medoids.

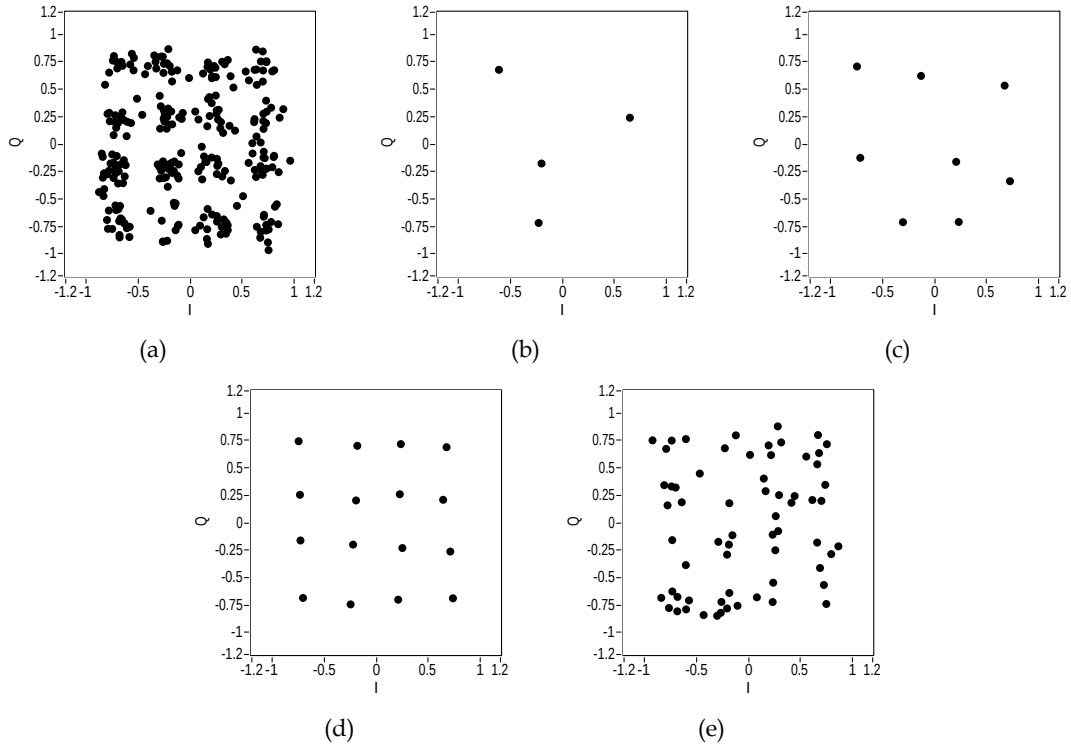


Figure 5.2 : (a) Constellation of 16-QAM at 13dB. Blind estimation of (b)4 medoids (c) 8 medoids (d)16 medoids (e)64 medoids

Step2 : All points other than these chosen k points are assigned to one of the medoids using any distance metric.

Step3 : One of the non-medoid is selected, and the total cost of swapping is calculated. If this cost of swapping is greater than the cost of the previous medoid, then previous points are retained as medoids; else, they are replaced.

Step4 : Repeat steps 2 and 3 until there is no change in medoids.

Blindly k medoids are estimated and compared to the ideal structure of constellation of different modulation schemes considered. Figure 5.2 shows k medoids calculated with k = 4, 8, 16, and 64 for input constellation of $16-QAM$. Similarity with the ideal structure of $QPSK$, $8-PSK$, $8-QAM$, $16-QAM$, and $64-QAM$ is calculated. Let η be a set consisting of k medoids i.e.,

$$\eta = \{\eta_1, \eta_2, \ldots, \eta_k\}$$

Then, similarity measure χ is given by

$$\chi = \frac{1}{\frac{1}{k}\sum_i \min_{\forall l \in \eta} D(x_i, \eta_l)} \tag{5.1}$$

Here $D(x,y)$ is the 2-norm distance between x and y. χ is calculated for all modulations under consideration simultaneously i.e., estimated k medoids are compared with ideal constellation points of all modulation schemes separately and compared with each other. The decision is given in favor of a modulation scheme for which a calculated χ is maximum. k for $QPSK$ is 4, for $8-QAM$ and $8-PSK$ is 8, for $16-QAM$ is 16 and for $64-QAM$ is 64. As χ is biased towards a higher-order modulation scheme, the mean of the 2-norm distance is taken for unbiased results.

5.2.2 Simulation results

In this section, results for the proposed method are evaluated for different SNR in the AWGN channel. They are also compared with some existing methods of modulation classification. Most of the methods in the literature require offline training of the system, while the method presented works without any training.

This section explains the accuracy of the classification of the proposed method. For all the modulation schemes, waveforms are generated for 1000 symbols using LabVIEW. A signal is passed through the AWGN channel. Figure 5.3 shows that all modulation schemes are classified with 100% accuracy above 13 dB SNR. QPSK, 8-PSK, and 8QAM are classified accurately above 9 dB SNR, while 16-QAM has classified accurately above 12 dB SNR and 64-QAM above 13 dB SNR. Table 5.1 shows the confusion matrix for all modulation schemes considered at 10 dB. From

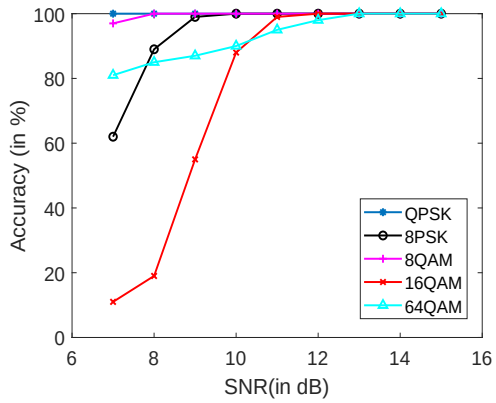


Figure 5.3 : Accuracy versus SNR for different modulation schemes.

Table 5.1 : Confusion matrix for different considered modulation schemes

	QPSK	8-PSK	8-QAM	16-QAM	64-QAM
QPSK	100	0	0	0	0
8-PSK	0	100	0	0	0
8-QAM	0	0	100	0	0
16-QAM	0	0	0	88	12
64-QAM	0	0	0	10	90

the table, it is clear that QPSK, 8PSK, 8QAM are identified correctly, while 16QAM is sometimes identified as 64-QAM and vice versa as they share a similar structure.

5.2.3 Comparison to related work

Table 5.2 compares the proposed work with the Naive and SVM classifier [Wong *et al.*, 2008]. Accuracy by these methods is evaluated between four modulation schemes i.e., QPSK, 8-PSK, 16-QAM, and 64-QAM. A comparison table has been made according to these modulation schemes for a fair comparison. It shows that at 16 dB SNR, the Naive classifier achieves an accuracy of 96.66 % and SVM achieves 97.89% compare to our method, which achieves 100% accuracy. Naive and SVM classifier does not achieve 100% even at 20 dB SNR while the proposed method achieves it at 15 dB SNR.

Table 5.2 : Comparison of Naive classifier and SVM with proposed classifier

N	SNR	Probability of correct classification		
		Naive	SVM	k-Medoids
1024	16	96.66	97.89	100
	18	97.29	98.65	100
	20	98.05	98.89	100
2048	16	99.42	99.26	100
	18	99.4	98.36	100
	20	99.66	99.4	100

Table 5.3 compares KNN, GP-KNN, and GP-tree classifier [Aslam *et al.*, 2012] with the proposed method. At 1024 symbol length and 15 dB SNR, the present method's accuracy is 100% compared to KNN, GP-KNN, and GP-tree, which manages to achieve 97, 99, and 99.31% accuracy, respectively. It shows that the present method outperforms these more complex methods, which require training.

Table 5.3 : Comparison of KNN, GP-KNN, GP-tree and proposed classifier

N	SNR	Probability of correct classification			
		KNN	GP-KNN	GP-tree	k-Medoids
1024	15	97	99	99.31	100
	20	98	100	99.55	100
2048	15	100	100	-	100
	20	100	100	-	100

5.3 CLASSIFICATION USING K MEDOIDS AND INSTANTANEOUS PHASE IN FLAT FADING CHANNEL

While the previously developed algorithm was analyzed in AWGN, this method was developed for slow and flat fading channels described in Section 2.1.2. The symbol rate has been estimated according to Section 3.3.2. Constellation points are extracted after matched filtering and downsampling. After extracting the constellation points, the proposed algorithm estimates the modulation domain, i.e., PSK or QAM followed by phase offset estimation and correction. After correcting the phase offset, the modulation order is estimated.

5.3.1 Modulation Domain Identification

To differentiate between QAM and PSK domain, a feature based on the amplitude of the medoids calculated using k-medoids clustering is used. Nine medoids are calculated from constellation points, and the amplitudes of all medoids are sorted in ascending order. The standard deviation (SD) of the contiguous amplitude difference (represented by a) is calculated and compared with the threshold ($a_{th} = 0.26$) for classification of the domain, i.e., QAM and PSK. The value of the threshold has been set using monte Carlo simulations. With a higher value of a_{th}, it becomes biased towards the PSK domain. Similarly, for the lower value of the threshold, the classifier becomes biased towards QAM modulation. Hence, from simulations, a value of $a_{th} = 0.26$ gives the maximum accuracy which is also shown in Figure 5.4. This graph is obtained by finding

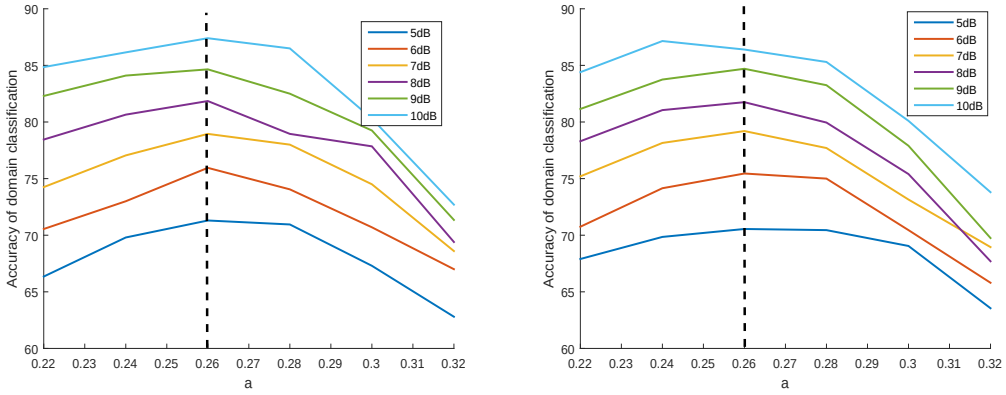


Figure 5.4 : Accuracy of domain classification with changing threshold value (a) (a) in AWGN (b) in slow and flat fading.

accuracy for correct domain classification at different SNR values over different values of a. All the simulations are done over 1000 signals with 1000 symbols in each signal. Modulations considered for these graphs are BPSK, QPSK, 8PSK, and 16QAM.

5.3.2 Phase offset estimation

If the domain classified is QAM, i.e., for $a > a_{th}$, the phase offset is estimated using Equation (3.42) [Cartwright, 1999] explained in Section 3.3.4, but this method fails for PSK. Hence, a new method for phase offset estimation of PSK modulation is proposed. For PSK, the phase offset is estimated and corrected using Equation (3.47) explained in Section 3.3.4.

5.3.3 Modulation Scheme Estimation

Phase offset corrected constellation points are given to the proposed algorithm shown in Figure 5.5. If PSK modulation is observed, 16 medoids are estimated using k medoids clustering. Figures 5.6(a) and (b) shows the phase offset corrected BPSK and QPSK constellation, respectively. Figures 5.6(c) and (d) shows 16 estimated medoids for Figures 5.6(a) and (b), respectively. Phases of all 16 medoids are sorted in ascending order. The contiguous difference of sorted phases is calculated and again sorted in ascending order. If the number of differences between 30^0 and 60^0 is greater than 4, the decision is given in favor of 8-PSK. Otherwise, the number of points after a rise provides an estimate of modulation order 4 or 2, i.e., QPSK or BPSK, as shown in Figures 5.6(e) and (f), respectively.

If the domain falls under QAM, the constellation points of all four quadrants are considered separately for the estimation of order. The set of points in each quadrant is shifted to zero mean. In the first step, QAM is tested for order 64. Each quadrant point of 64-QAM is tested for 16-QAM. If more than two sets give a decision as 16-QAM, the classification result is given in favor of 64-QAM. Figure 5.7 shows the method to classify 64-QAM. If the decision is not in favor of 64-QAM, constellation points are tested for 16-QAM. The idea is to test each quadrant points for QPSK. Points in each quadrant are shifted to zero mean, and eight medoids are estimated. These shifted medoids are tested for QPSK as points in each quadrant of the 16-QAM constellation has a structure similar to QPSK. Figure 5.8 shows the $four$ sets denoted by $Q1$, $Q2$, $Q3$, $Q4$ for each quadrant and testing of $Q4$ for QPSK. If 3 or more quadrant points are identified as QPSK, the classification result is given

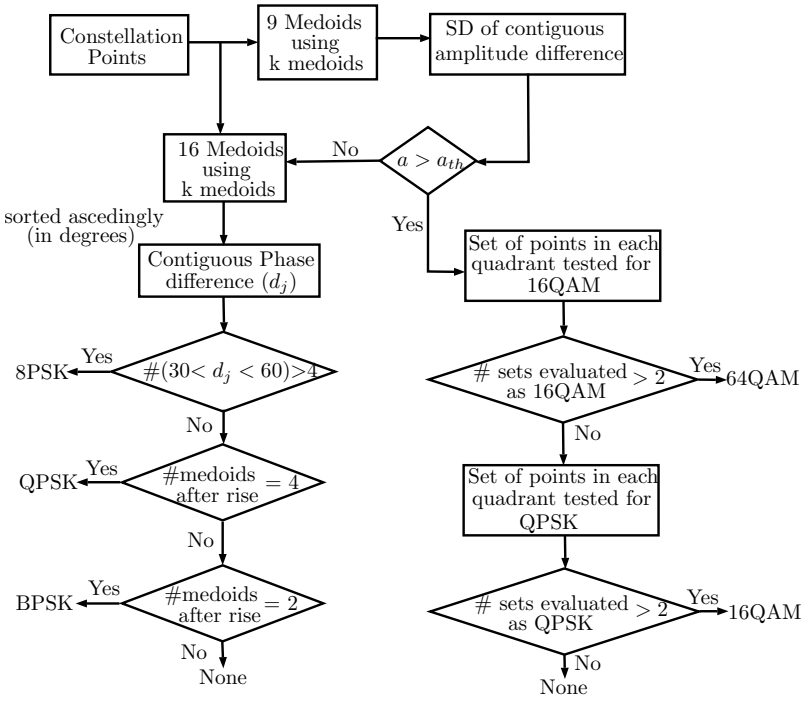


Figure 5.5 : Block diagram of modulation classification algorithm.

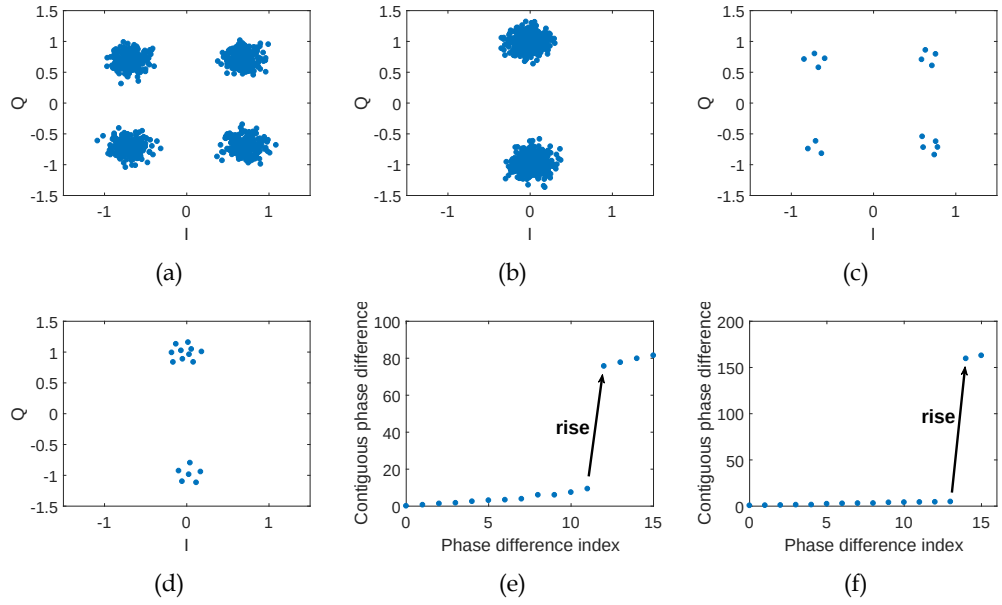


Figure 5.6 : Constellation at 15dB of (a) QPSK and (b) BPSK. Blind 16 medoids estimated (c) from 5.6(a) and (d) from 5.6(b). Contiguous phase differences for (e) medoids estimated in 5.6(c) and (f) medoids estimated in 5.6(d).

in favor of 16-QAM.

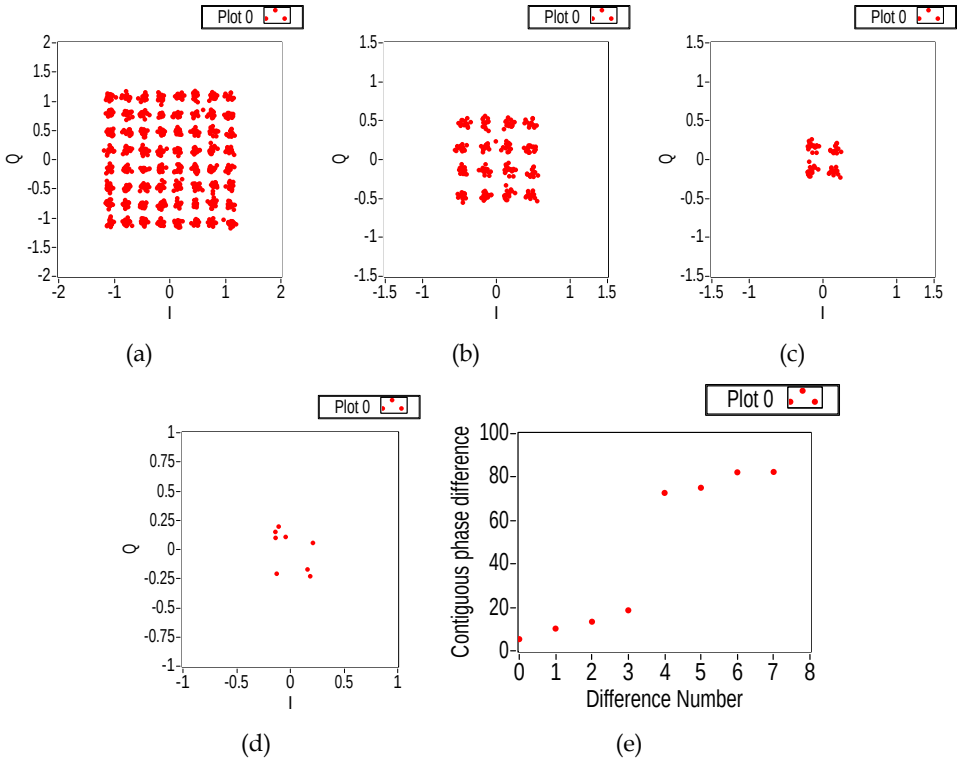


Figure 5.7 : (a)Constellation of 64-QAM at 25dB. (b)Zero centered first quadrant points of Figure 5.7(a) for 16-QAM testing (c)Fourth quadrant point of Figure 5.7(b) for QPSK testing. (d)Estimated 8 medoids from Figure 5.7(c). (e)Graph for sorted contiguous phase differences.

5.4 RESULTS AND DISCUSSION

In this section, the probability of correct classification P_{cc} of the proposed AMC algorithm is assessed through Monte Carlo simulations in LabVIEW. Results obtained are compared with different classifiers used in the literature. The modulation candidate set comprises BPSK, QPSK, 8-PSK, 16-QAM, and 64-QAM. In each trial, P_{cc} is calculated for 1000 recovered random symbols from modulation over 1000 signal realizations for every SNR. All signals are subjected to AWGN and Rayleigh fading with slow phase offset varying uniformly between 0 and 2π.

Figure 5.9(a) shows the accuracy of different modulation schemes with SNR under the AWGN channel. BPSK, QPSK, and 8-PSK have been identified accurately above 8dB, 9dB, and 12dB SNR respectively, while 16-QAM is identified reliably ($>$ 90%) above 14dB SNR. In the accuracy curve of 8-PSK, there is a dip caused by the same phase and different amplitude of the esitmated medoids at lower SNR. At higher SNR, estimated medoids are on a circle with values of contiguous phase difference less than 30^0 due to which accuracy decreases slightly. 64-QAM is classified with an accuracy of 90.7% at 21dB in the AWGN channel, and in the fading environment, 89.1% accuracy is achieved at 30dB. Figure 5.9(b) shows the result of classification accuracy for the fading environment.

Figure 5.9(c) compares the proposed algorithm with GP-KNN in the AWGN channel over four classes, i.e., BPSK, QPSK, 8-PSK, and 16-QAM for 512 symbols. For SNR higher than 12dB, the proposed method achieves greater accuracy compared to GP-KNN. Further, the proposed method is also compared with the algorithm given in [Chen *et al.*, 2019] for the same set of GMM models. It also works better at higher SNR. In [Hazar *et al.*, 2018], spectral and statistical features are used along with different classifiers like ANN, SVM, k-NN, logistic regression, and gradient

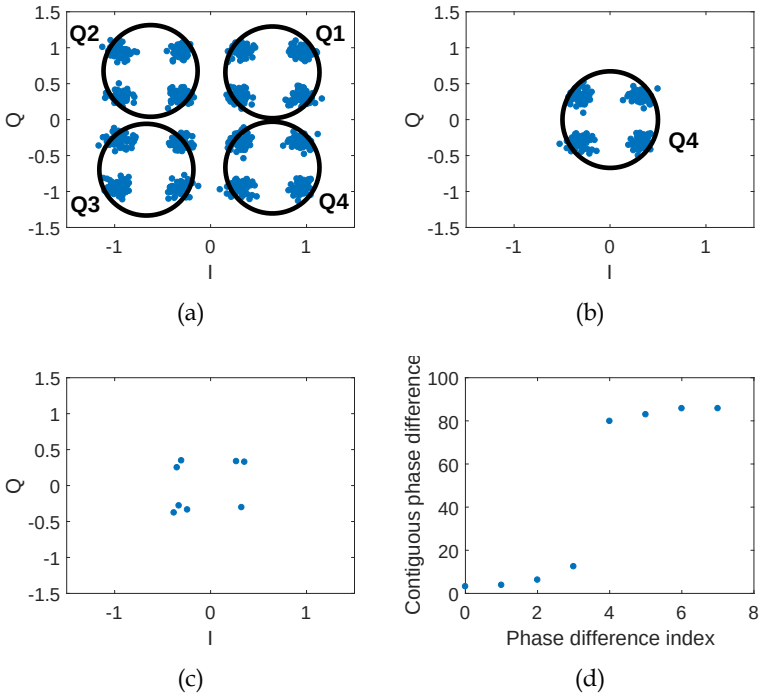


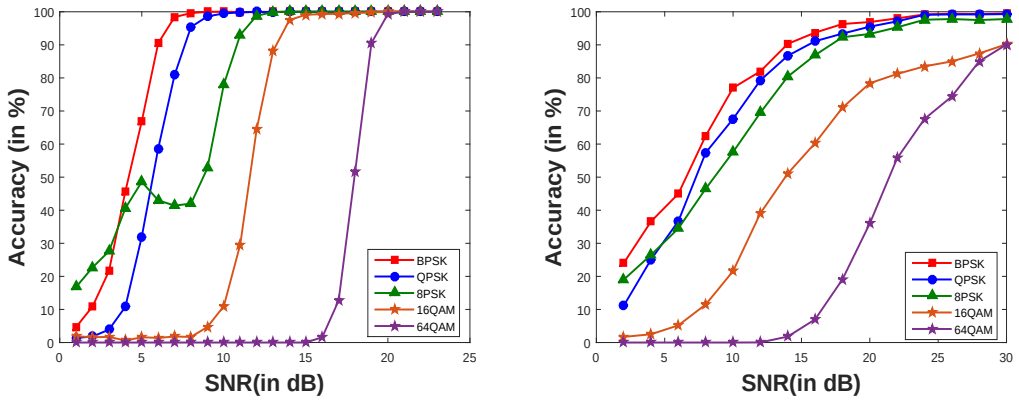
Figure 5.8 : (a) 16-QAM constellation at 20dB. (b) Fourth quadrant points with zero mean. (c) 8 estimated medoids from 4(b). (d) Contiguous phase difference of 4(c).

boosted regression tree (GBRT). Table 5.4 compares the results given in [Hazar *et al.*, 2018] with the proposed classifier for BPSK, QPSK, 8-PSK, and 16-QAM in Rayleigh fading channel without diversity. Table 5.4 shows that the accuracy of the proposed method is higher for all modulations and classifiers except for BPSK with the Naive and Logistic regression classifier.

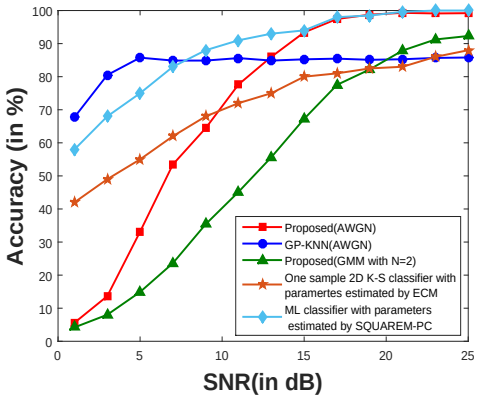
Table 5.4 : Comparison between different classifiers given in [Hazar *et al.*, 2018] and proposed work at 20dB SNR

	Naive	ANN	Logistic reg.	GBRT	Proposed
BPSK	99.6	20	98.2	96.4	96.9
QPSK	61.4	56.4	54.8	33.4	95.5
8-PSK	16.2	22.6	34.4	57.2	93.3
16-QAM	60.8	43.4	61.6	56.4	78.4

In [Aslam *et al.*, 2012], 16-QAM is classified using fourth and sixth order cumulants with an accuracy of 98.7% at 15 dB with GP-Tree classifier while our method achieves 99.28% without any training. In [Abdelmutalab *et al.*, 2016], the polynomial classifier with higher-order cumulants is used which needs to optimize the weights at each hierarchy of the binary classification. For AWGN channel with unknown SNR, Conventional and Hierarchical Polynomial classifiers achieve the accuracy of 84% and 91% at 20dB SNR respectively, while the proposed method provides a classification accuracy of 99.82% which shows that the proposed method performs better than these classifiers.



(a) (b)



(c)

Figure 5.9 : Accuracy of BPSK, QPSK, 8-PSK, 16-QAM, and 64-QAM in (a) AWGN channel and (b) Fading channel. (c) Comparison of proposed algorithm with GP-KNN, K-S, and ML classifiers in Gaussian Mixture Model.

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