

KNN BASED CLASSIFICATION OF DIGITAL MODULATED SIGNALS

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ABSTRACT:Demodulation process without knowledge of the modulation scheme requires Automatic Modulation Classification (AMC). When the receiver has limited information about the received signal, AMC becomes an essential process. AMC has an important place in many civil and military fields such as modern electronic warfare, interfering source recognition, frequency management, link adaptation, etc. In this paper, we explore the use of K-nearest neighbor (KNN) for modulation classification with different distance measurement methods. Five modulation schemes are used for classification purposes which are Binary Phase Shift Keying (BPSK), Quadrature Phase Shift Keying (QPSK), and Quadrature Amplitude Modulation (QAM) as both 16-QAM and 64-QAM. Higher order cumulants (HOC) are used as an input feature set to the classifier. Simulation results show that the proposed classification method provides better results for the considered modulation formats.

ABSTRAK:Proses Demodulation tanpa ilmu mengenai skim modulasi memerlukan Klasifikasi Modulation Automatik (AMC). Apabila penerima mempunyai maklumat yang terhad mengenai signal yang diterima, maka AMC menjadi proses yang penting. AMC adalah penting didalam pelbagai bidang sivil dan ketenteraan seperti peperangan elektronik moden, gangguan di dalam pengiktirafan sumber, pengurusan kekerapan, penyesuaian pautan dan lain-lain. Dalam kertas ini kami meneroka penggunaan jiran K-terdekat (KNN) bagi klasifikasi modulasi dengan kaedah pengukuran jarak yang berbeza. Lima skim modulasi digunakan untuk tujuan mengklasifikasi adalah Penguncian Anjakan Fasa Biner (BPSK), Penguncian Anjakan Fasa Quadrature (QPSK), Quadrature Pemodulatan Amplitud (QAM), 16-QAM dan 64-QAM. Cumulants paras tinggi (HOC) digunakan sebagai set ciri input yang ditetapkan untuk pengelasan. Hasil simulasi menunjukkan bahawa cadangan kaedah pengelasan memberi keputusan yang lebih baik untuk format modulasi yang dipertimbangkan.

KEYWORDS:automatic modulation classification (AMC); higher order cummulants (HOC); K-nearest neighbor (KNN); QAM and QPSK

1. INTRODUCTION

Automatic modulation classification is a procedure performed at the receiver based on the received signal before demodulation when the modulation format is unknown to the receiver. It plays a key role in various tactical communication applications. It also finds applications in emerging wireless communication systems that employ interference cancelation techniques in order to demodulate and cancel the unknown interfering user's

signal. In the interference application, the signal's modulation format needs to be classified first. The solution to the problem of AMC strongly relies on one of the two approaches i.e. the likelihood-based (LB) [1, 2] and the feature-based (FB) AMC[3, 4].

The LB approach performs AMC-based on the likelihood function of the received signal, by which modulation classification can be formulated as a multiple hypothesis test problem with multiple unknown modulation parameters [5]. The LB-based AMC approach can theoretically reach the optimum solution in the Gaussian condition, but at a cost of computational complexity. Moreover, its performance is affected by model mismatch in the presence of carrier frequency offsets, phase errors, timing errors, and residual channel effects. In contrast, the FB approach is sub-optimal in performance but very feasible in real-time implementation.

The FB-based AMC approach mainly extracts reference features from the received signal and makes decisions from the calculated features based on the theoretical values for different modulation parameters. In brief, the FB approach benefits from lower computational complexity, with better efficiency and less sensitivity to possible model mismatches. In the FB approach, three features are often discussed in the literature: instantaneous information [6, 7], wavelet coefficients [8–10] and high-order statistics (HOS) [11–15]. The instantaneous information may include the instantaneous amplitude, phase, or frequency of the incoming signal. These features are the most intuitive ones with less complex implementation. However, they are sensitive to additive noises and the residual channel effects. Moreover, the extraction of instantaneous information relies on thresholds that are set in advance. The wavelet coefficients can be obtained through a Haar wavelet transform by transforming the signal into its wavelet coefficients. Modulation classification with wavelet coefficients has better resistance to the noise at the cost of higher complexity, compared with that with instantaneous information. HOS is a more frequently adopted feature than the previous two, generally including the statistics of moments and cumulants [16–18]. In addition to classification of the modulation types, HOS can distinguish modulation orders with high resistance to the additive white Gaussian noise (AWGN) as well. Furthermore, the multipath channel effects can be easily modeled using the HOS method [19–21].

Most of the previous research work on AMC has focused on the modulation classification techniques in AWGN. Actually, the correctness of modulation classification is seriously degraded subject to the multipath fading effect in wireless channels. The pioneer work by Wu et al. [20] derived a relationship between the normalized channel coefficients and the normalized fourth-order cumulants. Through their formulation, the classification of the transmitted modulated symbols can be obtained from the normalized fourth-order cumulants of the received signal. The blind channel estimation method using higher-order cumulants was then adopted in [22, 23] to improve the classification performance in cases of non-dispersive channels and one-dominant-path channels. In literature, a tree-structured modulation classification scheme [24, 25] based on three normalized fourth-order cumulants is also used for the same work.

In this paper, HOS was used for the modulation classification purpose; eleven eighth-order cumulants have been used throughout the research. The features are extracted for the noisy (AWGN) signals. The modulation schemes used here are BPSK, QPSK, QAM, 16QAM, 64QAM for a KNN classifier with different distance measurement methods i.e. Euclidean distance, Correlation distance, Minkowski distance, and Mahalanobis distance.

The rest of the paper is organized as follows: Section 2 describes the system model and Feature Extraction. Section 3 explains the classification methodology. Section 4 gives

a comparative analysis of the KNN classifier for five modulations using different distance methods under different SNRs. Conclusion and future work is presented in section 5.

2. SIGNAL MODEL AND FEATURE EXTRACTION

2.1 Signal Model

An AWGN channel was used for these simulations. Thus, the received signal is only impaired by additive white Gaussian noise. Figure 1 shows the system model. The generalized expression for signal received is given by [26].

$$r(n) = s(n) + y(n) \quad (1)$$

where $r(n)$ complex baseband is the envelope of the received signal, $y(n)$ is the additive white gaussian noise and received signal $s(n)$ is given by

$$s(n) = K e^{i(2\pi f_o n T + \theta_n)} \sum_{j=-\infty}^{\infty} s(j) h(nT - jT + \epsilon_T T) \quad (2)$$

where, $s(j)$ is the input symbol sequence which is drawn from the set of M constellations of known symbols, not necessarily equi-probable. K is the amplitude of the signal, f_o is the frequency offset constant, T is the symbol spacing, θ_n is the phase jitter which varies from symbol to symbol, $h(\dots)$ represents channel effects, and ϵ_T is the timing jitter.

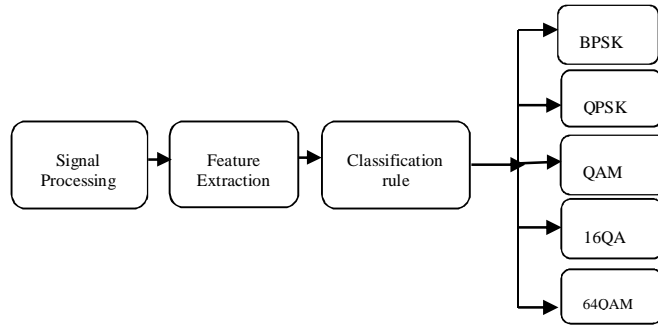


Fig. 1: System model for modulation classification.

2.2 Feature Extraction

Cumulants are made up of moments which are used here as features. For the complex valued stationary random process $r(n)$, cumulants of the 2nd, 4th, 6th and 8th order are as follows[27]:-

$$C_{20} = E[y^2(n)] = cum\{y(n), y(n)\} \quad (3)$$

$$C_{21} = E[|y(n)|^2] = cum\{y(n), y^*(n)\} \quad (4)$$

$$C_{40} = M_{40} - 3M_{20}^2 = cum\{y(n), y(n), y(n), y(n)\} \quad (5)$$

$$C_{41} = M_{40} - 3M_{20}M_{21} = cum\{y(n), y(n), y(n), y^*(n)\} \quad (6)$$

$$C_{42} = M_{42} - |M_{20}|^2 - 2M_{21} = cum\{y(n), y(n), y^*(n), y^*(n)\} \quad (7)$$

$$C_{60} = M_{60} - 15M_{20}M_{40} + 30M_{20}^3 = cum\{y(n), y(n), y(n), y(n), y(n), y(n)\} \quad (8)$$

$$C_{61} = M_{61} - 5M_{21}M_{40} - 10M_{20}M_{41} + 30M_{20}^2M_{21} \quad (9)$$

$$\begin{aligned}
&= \text{cum}\{y(n), y(n), y(n), y(n), y(n), y^*(n)\} \\
C_{62} &= M_{62} - 6M_{20}M_{42} - 8M_{21}M_{41} - M_{22}M_{40} + 6M_{20}^2M_{22} + 24M_{21}^2M_{22} \\
&= \text{cum}\{y(n), y(n), y(n), y(n), y^*(n), y^*(n)\}
\end{aligned} \tag{10}$$

$$\begin{aligned}
C_{63} &= M_{63} - 9M_{21}M_{42} + 12M_{21}^3 - 3M_{20}M_{43} - 3M_{22}M_{41} + 18M_{20}M_{21}M_{22} \\
&= \text{cum}\{y(n), y(n), y(n), y^*(n), y^*(n), y^*(n)\}
\end{aligned} \tag{11}$$

$$\begin{aligned}
C_{80} &= M_{80} - 35M_{40}^2 - 28M_{60}M_{20} + 420M_{40}M_{20}^2 - 630M_{20}^4 \\
&= \text{cum}\{y(n), y(n), y(n), y(n), y(n), y(n), y(n), y(n)\}
\end{aligned} \tag{12}$$

$$\begin{aligned}
C_{84} &= M_{84} - 16C_{63}C_{21} + |C_{40}|^2 - 18C_{42}^2 - 72C_{42}C_{21}^2 - 24C_{21}^4 \\
&= \text{cum}\{y(n), y(n), y(n), y(n), y^*(n), y^*(n), y^*(n), y^*(n)\}
\end{aligned} \tag{13}$$

M_{pq} Stands for moments of received signal and it is given by

$$M_{pq} = E[y(k)^p y^*(k)^q] \tag{14}$$

The above cumulants are used to classify the BPSK, QPSK, QAM, 16QAM and 64QAM modulated signals in the presence of AWGN noise.

3. KNN CLASSIFIER

3.1 Introduction to KNN Classifier

KNN is a non parametric, slow adapting, and lazy algorithm in the sense that it does not make any assumptions on the underlying data distribution and requires more computations and memory. However, due to the non parametricness, KNN is well suited to practical real world problems as much of the acquired data does not agree with assumptions made in theory for mathematical convenience. This resembles the philosophy of SVM where non-support vectors can be omitted without sacrificing performance. KNN works with a minimal training phase, however, testing is performed over the whole testing data which requires more memory for its storage.

3.2 KNN Classifiers

The KNN classifier is used to compare the accuracy of extracted features from different modulation schemes. The eleven features are the Cumulants which have been extracted from the signal earlier. The method is quite simple. Firstly, a few values are used as sample data for the KNN classifier as there are eleven Cumulants and therefore eleven dimensional spaces for KNN. After this, some test values of these features are given to the KNN classifier and KNN calculates the distance of these samples from K neighbors' samples. The class having the maximum numbers of neighbors is considered to be the class of the test sample.

3.2.1 Euclidean Distance

$$d = \sqrt{\sum_{i=1}^{11} (x_i^s - y_i^t)(x_i^s - y_i^t)} \tag{15}$$

where x_i^s the i^{th} input is feature value and y_i^t is the test feature value.

3.2.2 Correlation Distance

$$d = \sum_{i=1}^{11} 1 - \frac{(x_i^s - \bar{x}_i^s)(y_i^t - \bar{y}_i^t)}{\sqrt{(x_i^s - \bar{x}_i^s)(x_i^s - \bar{x}_i^s)} \sqrt{(y_i^t - \bar{y}_i^t)(y_i^t - \bar{y}_i^t)}} \quad (16)$$

where x_i^s is the i th input feature value and y_i^t is the test feature value and furthermore,

$$\bar{x}_i^s = \frac{1}{n} \sum_j x_{sj} \quad \text{and} \quad \bar{y}_i^t = \frac{1}{n} \sum_j y_{sj}$$

3.2.3 Mahalanobis Distance

$$d = \sqrt{\sum_{i=1}^{11} (x_i^s - y_i^t) C^{-1} (x_i^s - y_i^t)} \quad (17)$$

where x_i^s is the i th input feature value and y_i^t is the test feature value and C is the covariance matrix.

3.2.4 Minkowski Distance

$$d = \sqrt[p]{\sum_{j=1}^{11} |x_{sj} - y_{tj}|^p} \quad (18)$$

where x_i^s the i th input is feature value and y_i^t is the test feature value.

4. SIMULATION RESULTS

The modulation classification using KNN is evaluated in this section. Firstly, the input data -extracted features from the received signal and desired output signals- are used to make the classifier model, after which different distance techniques are used to classify the input signals. The performance using different distance measurement techniques for KNN under the influence of SNR and number of samples are given in the tables. Overall, 250 data samples were used at the training phase and 25 were used as test samples during the testing phase, in order to obtain the results shown in the table. The end result is an average of 10 iterations for each horizontal and vertical entry in the table.

4.1 KNN with Euclidean Distance

Table 1 compares the performance of the KNN classifier using Euclidean distance for digital modulations which are BPSK, QPSK, QAM, 16QAM and 64QAM with different number of samples. As can be seen in the table, the accuracy is enhanced with the increase of signal to noise ratio and number of samples. The performance accuracy for BPSK is 98.87%. Similarly, the performance accuracy table for QPSK demonstrates a classification accuracy of 99.73%. However, for the next modulation scheme, which is QAM, the performance accuracy is 96.80% and for 16QAM it is 99.70%. At last, the classification accuracy for 64QAM is found to be 99.57%.

Table 2: Percentage classification accuracy using KNN (Euclidean distance)

SIGNAL	No of SAMPLE	0dB	5dB	10dB
BPSK	512	88.08	98.97	100
	1024	98.49	99.98	100
	2048	99.95	100	100
	4096	100	100	100
QPSK	512	95.85	100	100
	1024	99.97	100	100
	2048	100	100	100
	4096	100	100	100
QAM	512	76	98	100
	1024	90.64	99.96	100
	2048	97.2	100	100
	4096	99.88	100	100
16QAM	512	97.87	99.41	99.73
	1024	99.89	99.99	100
	2048	100	100	100
	4096	100	100	100
64QAM	512	97.00	98.9	99.47
	1024	99	99.98	99.72
	2048	100	100	100
	4096	100	100	100

Table 2: Percentage classification accuracy using KNN (Correlation distance)

SIGNAL	No of SAMPLE	0dB	5dB	10dB
BPSK	512	93.95	99.99	100
	1024	99.8	100	100
	2048	98.29	100	100
	4096	99.95	100	100
QPSK	512	94.5	99.3	100
	1024	94.58	99.68	100
	2048	95.26	99.70	100
	4096	96.35	99.79	100
QAM	512	60.23	73.5	97
	1024	71.92	82.19	97.99
	2048	80.27	93.3	99.91
	4096	87.05	93.57	100
16QAM	512	80.33	90.3	93
	1024	81.59	87.07	95.5
	2048	83.24	92.45	96.73
	4096	93.23	97.86	100
64QAM	512	80.33	93.65	95
	1024	87.94	94.98	96.39
	2048	89.93	96.91	98.17
	4096	90.43	97.83	100

4.2 KNN with Correlation Distance

Table 2 compares the performance of the KNN classifier using correlation distance for digital modulations which are BPSK, QPSK, QAM, 16QAM and 64QAM with different number of samples. As can be seen in the table, the accuracy is enhanced with the

increase of signal to noise ratio and number of samples. The performance accuracy for BPSK is 98.33 %. Similarly, the performance accuracy table demonstrates that the classification accuracy for QPSK is 67.53%. However, for the next modulation scheme, which is QAM, the performance accuracy is 71.11% and the accuracy for 16QAM is 41.29 %. At last, the classification accuracy for 64QAM is found to be 41.17%.

4.3 KNN with Minkowski Distance

Table 3 compares the performance of the KNN classifier using Minkowski distance for digital modulations which are BPSK, QPSK, QAM, 16QAM and 64QAM with different numbers of samples. As can be seen in the table, the accuracy is enhanced with the increase of signal to noise ratio and number of samples. The performance accuracy for BPSK is 99.53 %. Similarly, the performance accuracy table demonstrates that for QPSK, the classification accuracy is 99.95%. However, for the next modulation scheme, which is QAM, the performance accuracy is 99.38% and for 16QAM it is also 99.79%. At last, the classification accuracy for 64QAM is found to be 99.63% which is same as QPSK, QAM and 64QAM.

Table 3: Percentage classification accuracy using KNN (Minkowski distance)

SIGNAL	No of SAMPLE	0dB	5dB	10dB
BPSK	512	95.2	100	100
	1024	99.23	100	100
	2048	100	100	100
	4096	100	100	100
QPSK	512	96.4	99.8	100
	1024	99.98	100	100
	2048	100	100	100
	4096	100	100	100
QAM	512	79.96	99.28	100
	1024	90.62	99.93	100
	2048	98.91	100	100
	4096	99.92	100	100
16QAM	512	98.63	99.48	99.53
	1024	99.95	100	100
	2048	100	100	100
	4096	100	100	100
64QAM	512	97.33	99.78	100
	1024	99.95	99.96	100
	2048	97.2	100	100
	4096	99.88	100	100

4.4 KNN with Mahalanobis Distance

Table 4 compares the performance of the KNN classifier using Mahalanobis distance for digital modulations which are BPSK, QPSK, QAM, 16QAM and 64QAM with different numbers of samples. As can be seen in the table, the accuracy is enhanced with the increase of signal to noise ratio and number of samples. The performance accuracy for BPSK is 99.95 %. Similarly, the performance accuracy table demonstrates that the classification accuracy is 99.97% for QPSK. However, for the next modulation scheme, which is QAM, the performance accuracy is 99.97% and for 16QAM it is also 99.91%. At last, the classification accuracy for 64QAM is found to be 99.87%.

Table 4: Percentage classification accuracy using KNN (Mahalanobis distance)

SIGNAL	No of SAMPLE	0dB	5dB	10dB
BPSK	512	97.56	99.96	100
	1024	99.80	100	100
	2048	99.92	100	100
	4096	100	100	100
QPSK	512	97.84	99.92	99.96
	1024	99.92	100	100
	2048	100	100	100
	4096	100	100	100
QAM	512	99.68	99.84	100
	1024	99.76	99.84	100
	2048	99.96	99.80	100
	4096	100	100	100
16QAM	512	98.63	99.92	100
	1024	99.88	99.88	99.92
	2048	99.80	99.92	99.96
	4096	100	100	100
64QAM	512	97.84	99.88	100
	1024	99.88	99.88	99.88
	2048	99.84	99.92	99.92
	4096	99.80	99.92	99.88

4.5 Average Classification Performance

Table 5 shows the overall performance accuracy of each modulated signal with different distance measurement method for the KNN classifier. Each column represents the distance measurement technique and rows show the modulation scheme which was used in this paper. The performance of KNN with Euclidean distance was excellent for almost every modulation technique used. A 98.87% performance accuracy was achieved in the case of BPSK, and for QPSK it was 99.73%. QAM showed 96.80% performance accuracy, for 16QAM it was 99.70%, and for 64QAM performance accuracy was 99.57%. However, the correlation distance showed moderate results in comparison to other distance methods used. In the case of BPSK, a 99.33% accuracy was obtained. For 16QAM, the accuracy was 90.94%. Moreover, QPSK, QAM, and 64 QAM obtained 98.26%, 86.41%, and 93.46% respectively. KNN with Minkowski distance gave excellent results in all means; which is evident from the above table. 64QAM was classified with an accuracy of 99.63% and BPSK, QPSK, QAM, and 16QAM showed accuracies of 99.53%, 99.95%, 99.38%, and 99.79% respectively. The Mahalanobis distance with KNN also showed very good results, 64QAM had a low performance of 99.87%, while QPSK and QAM had maximum performance with 99.97%.

Table 5: Average Classification performance accuracy for KNN with used distance measurement approaches

Modulation Type	Euclidean	Correlation	Minkowski	Mahalanobis
BPSK	98.87 %	99.33%	99.53 %,	99.95 %
QPSK	99.73%	98.26%.	99.95%.	99.97%.
QAM	96.80%	86.41%	99.38%	99.97%
16QAM	99.70%	90.94%	99.79%.	99.91%.
64QAM	99.57%	93.46%.	99.63%	99.87%.

4.6 Comparison of Classification Accuracy with Different Distance Methods

This subsection presents the comparison of percentage of classification accuracy versus different SNR values under different distance methods. Due to limitations of space, graphs are presented in Fig. 2 to Fig. 6 for all 512 samples for the cases of BPSK, QPSK, QAM, 16 QAM and 64 QAM modulation schemes.

It can be clearly observed that the Mahalanobis distance method produces higher classification accuracy percentage compared to Euclidean, Correlation, and Minkowski distance methods for all modulation schemes under consideration. The correlation distance method is shown to have performed poorly compared to all other distance methods for all schemes other than BPSK. In the case of a BPSK modulation scheme, the correlation distance method out-performed the Euclidean distance method. However, overall the correlation method is shown to be the least performing of all distance methods.

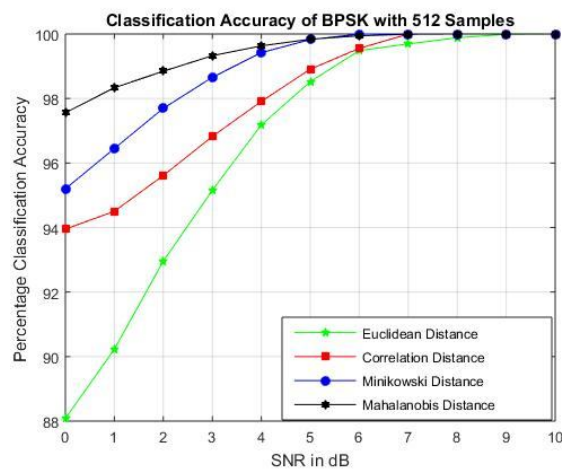


Fig. 2: Classification accuracy of BPSK modulation scheme for 512 samples with different SNR and distance methods.

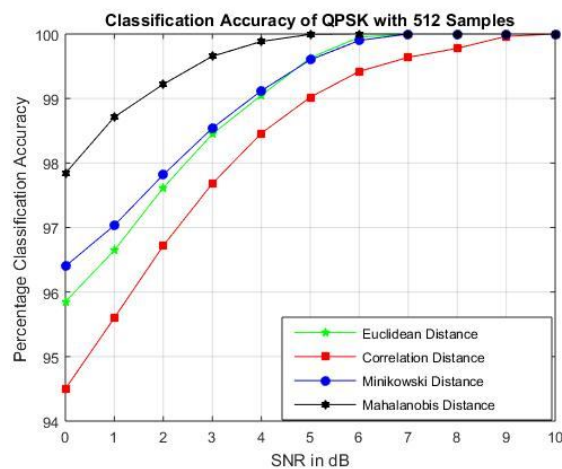


Fig. 3: Classification accuracy of QPSK modulation scheme for 512 samples with different SNR and distance methods.

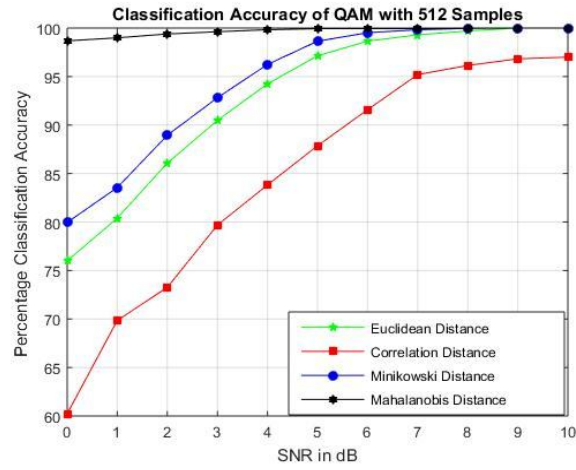


Fig. 4: Classification accuracy of QAMmodulation scheme for 512 samples with different SNR and distance methods.

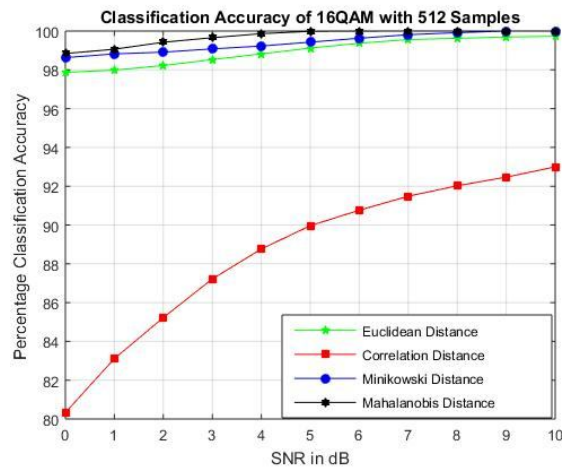


Fig. 5: Classification accuracy of 16QAMmodulation scheme for 512 samples with different SNR and distance methods.

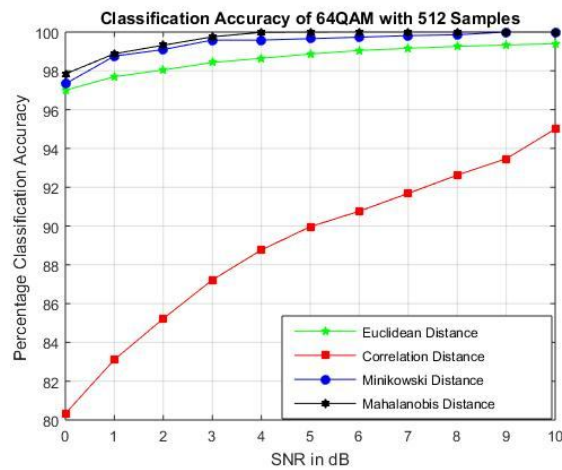


Fig. 6: Classification accuracy of 64QAMmodulation scheme for 512 samples with different SNR and distance methods.

5. CONCLUSION AND FUTURE WORK

In this paper, a classifier was proposed based on KNN using different distance methods on the sample data, in which HOC was used to extract features from the received signal under influence of SNR combined with an AWGN channel. Eleven eighth-order features were used for five different modulation schemes, namely BPSK, QPSK, QAM, 16QAM and 64QAM to be classified. Average performance accuracy was calculated with different SNR and number of samples which showed that the Mahalanobis distance method had a slight edge over the Minkowski method in terms of accuracy. Euclidean distance-based KNN classifier fell behind the aforementioned two distance methods classifiers. Correlation distance gave the least performance accuracy, making it unusable for classification.

In future, normalized cumulants can be used for feature extraction and GP for the new sample data generation with KNN as a fitness evaluator to improve the performance accuracy. Different channels and different modulation schemes can be used for the same problem.

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