

## AUTOMATIC MODULATION CLASSIFIER: A REVIEW

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Received:11/07/2020, Accepted:29/08/2020

**Abstract-** The automatic modulation classification (AMC) is highly important to develop intelligent receivers in different military and civilian applications including signal intelligence, spectrum management, surveillance, signal confirmation, monitoring, interference identification, as well as counter channel jamming. Clearly, without knowing much information related to transmitted data and various indefinite parameters at receiver, like timing information, carrier frequency, signal power, phase offsets, and so on, the modulations blind identification has been a hard task in the real world situations with multi- path fading, frequency-selective in addition to the time-varying channels. There are 2 methods could be utilized to decide the classification signal technique: Feature-based (FB) approach and the Maximum likelihood functions (LB) method. With regard to the FB (referred to as pattern-recognition) classification method used in the study. In the presented work, thorough study is provided to find easy method to identify and classify the digital modulation signals at low SNRs. Spectral-based features, high-order statistic features, wavelet-based features, also cyclic features on the basis of cyclostationary typically utilized to determine and discriminate modulation types have been examined. The number of the classifiers which have been utilized in the process of discrimination have been studied thoroughly and compared for helping researchers in determining and finding the drawbacks with pattern-recognition according to past works. The presented study serving as guide with regard to studies of AMC for determining adequate algorithms and features.

**keywords:** Linear classification schemes, Genetic algorithm, Automatic modulation classification, K-nearest neighbor, Feature-based, Likelihood-based, Artificial neural networks, Higher-order statistical, Support vector machine, Linear regression, Continuous wavelet transform, Genetic programming, Fast fourier transform.

### I. INTRODUCTION

With the elevated numbers of the wireless devices, (RF) spectrum has been congested more and more. Also, the spectrum sharing with the use of cognitive radio is going to be maximizing the use of current spectrum. A significant functionality related to cognitive radio has been detecting the available spectrum (for instance, spectrum holes) through identification and classification regarding primary user signals. Moreover, classification and detection of signals has been of high importance to many military and civilian applications, like threat detection, authentication, dynamic spectrum access (DSA), and so on. The detection and classification of signals have been difficult tasks, particularly in the noncooperative environments, in which certain factors such as fading, low SNR, interference, frequency and phase offsets resulting in distortions for received signals [1]. AMC is of high importance in noncooperative and cooperative communication applications. The general modulation classifiers operating in the noncooperative environments, indicating that the receiver has not much knowledge regarding transmitted signals, also not trainings are provided. Thus, practical modulation classifier must have the ability for working with conditions of asynchronous transmission [2]. Briefly, the noncooperative communications has been in the case when the desired signal come from transmitter which has no intention for the data for being interpreted through observing radio. In general, this is more difficult in comparison to cooperative communications where certain properties related to incoming signal might be specified a priori, like coding approach, which might be utilized with regard to more effective performance in the MC [3]. Therefore, the algorithms of AMR received significant focus as interesting and new are of

research. Fig. 1 showing the important role of AMC diagram. Front-end representing signal preprocessing block that is identifying the signal transmission. The presented block has been followed via AMC containing feature extractor which involve instantaneous amplitude, frequency, and phase, the statistical characteristics including high order moments as well as cumulants, spectral peaks, wavelets, and so on. The classifier block using the extracted features for identifying the signal modulation through utilizing fixed threshold, or utilizing the approach of pattern recognition, like SVMs or ANNs [4] . There are 2 classes related to the algorithms of AMC which might be crystallized, FB, and LB approaches [5] . Initially, LB modulation classifiers have been the major modulation classification method. The interests in the LB classifiers has been encouraged via the optimality related to the classification accuracy in the case when optimum channel model in addition to channel parameters have been recognized to classifiers (Ramezani-Kebrya et al. , 2013, Huang & Polydoros, 1995. Wei & Mendel, 2000, Sills, 1999, Hameed Dobre & Popescu, 2009) [6] . The major method related to LB modulation classifier includes 2 phases. With regard to the initial phase, the possibility has been estimated for all modulation theory with the specified signal samples. The possibility functions have been obtained from chosen signal model, also could be changed for fulfilling the requirement for reducing computational complexity or being practical in the noncooperative environments. With regard to the second phase, the possibility of various modulation hypothesizes have been compared for concluding classification decision [6] . Likelihood-based approaches are of 3 categories involving hybrid likelihood ratio test (HLRT) , generalized likelihood ratio test (GLRT) , also average likelihood ratio test (ALRT) . ALRT estimating signals unknown parameters through handling them as arbitrary variables with recognized probability density functions (PDF) . Which has been adequate for all likelihood-based methods, yet it has been computationally complex. Therefore, ALRT has been utilized as theoretical upper bound with regard to the probability of adequate classification for the other approaches. GLRT applies maximum likelihood estimate for unrecognized quantities rather than managing them as random variables with recognized PDF. This has been not much computationally complex in comparison to ALRT, yet it has been not much adequate in comparison to ALRT, also suffering from the no ability for differentiating nested constellations like 65-QAM and 16-QAM completely. The 2 algorithms might be used together for creating HLRT. Furthermore, the variants related to HLRT have been closest to the real-time implementations with DLRT utilizing the only variant which was carried out in practical scenarios [3] . Feature-based approach will be extracting set of the descriptive values from signal differentiating each one of the signals. Such features might be including Wavelet Transform coefficients, Fourier Transform coefficients, or the two together. This method has been sub-optimal with regard to the possibility of the correct classification, yet reducing computational complexity to the real-time applications. Find optimal set of the features for adequately identifying the modulation was the focus of numerous studies. The major utilized feature has been the cumulants of the fourth-order, also the other cumulants of the high-order that might be easily distinguishing linear digital modulation approaches from one another in the low-SNR environment [3] . There are 2 properties related to fourth-order cumulants which will make them required candidates as features. Initially, cumulant of the sum related to the 2 independent distributions has been specified as the summation which is related to cumulants of 2 distributions. Second, cumulants related to order more than 3 for Gauss distribution has been 0. Which is why, the cumulants which are related to constellation with additive white Gauss noise has been cumulants regarding constellation points with no noise. With regard to the presented work, thorough survey

will be carried out on FB methods for the digital MR, that might be of high importance to readers searching for lucid information related to classifiers and features utilized in FB-AMR. The remaining parts of this study has been provided in the following way: AMRs signal model is presented in Section 2. FB method and its features, that have been utilized throughout classification presented in Section 3. Classifier algorithms of the PR presented in the Section 4. Performance analysis is presented in the Section 5. Lastly, the conclusions are presented in Section 6.

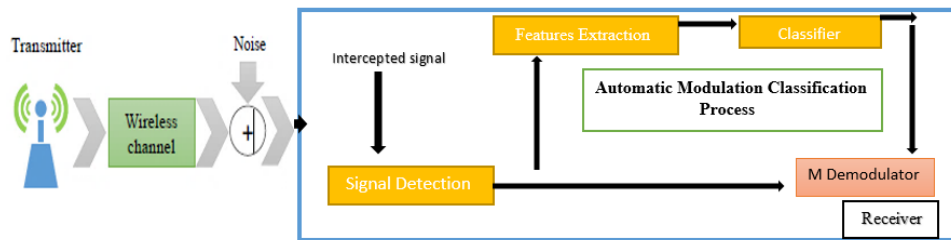


Figure 1: System model of AMC

## II. AMR SIGNAL

AMC has been considered as intermediate phase between demodulation and signal detection. With regard to hostile noncooperative environments, there is high importance in detecting friendly signals as well as demodulating them in a secure way, whereas the detection and the jamming (simultaneously) the intruder signal. Also, AMC is considered as significant element that help in detecting and classifying unknown signals. It might be exploiting SDRs flexibility as well as re-configuring the transceiver between different schemes of modulation with regard to spectrum or the channel condition. Due to the fact that feedback has been made available through transmitter before reconfiguration, intelligent transceiver that has been equipped with an AMC is going to be increasing the radios transmission efficiency through automating the process of reconfiguration with no requirement for feedback. Because of the noncooperative nature as well as real world cases, the AMC will be facing many challenges because of the unknown carrier frequency, frequency selective fading, signal power, phase offset, signal power, time offset, multipath fading, and so on [1] .

### A. Wireless channels and digital modulation

There have been 3 features related to sinusoidal wave which can be manipulated via the designer: phase, frequency, and amplitude. Certain scheme of modulation working on at least one of them. This work is going to specify 3 fundamental systems: QAM, FSK, and PSK.

#### 1) Phase Shift Keying (PSK).

This feature is working via allocating distinctive step to each one of symbols in baseband wave-form. Therefore, binary phase-shift keying (BPSK) where every one of the symbols representing single bit applies 2 distinctive steps, 4-PSK applies 4 distinctive steps, etc. The resulting waveforms might be specified in mathematical way via [7] :

$$S_i(t) = \begin{cases} \sqrt{\frac{2E_s}{T_s}} \cos \left[ 2\pi f_c t + \frac{2\pi}{M} i \right] & i = 0, 1, \dots, M - 1 \end{cases} \quad (1)$$

In which  $M$  representing the number of bits for each one of the symbols,  $f_c$  representing carrier frequency,  $E_s$  representing energy for each one of the symbols, also  $T_s$  representing symbol interval. The situation in which  $M = 4$  illustrating results which has been majorly utilized in the communications systems: orthogonal signaling. The 4 steps have been  $0, \frac{\pi}{2}, \pi, \text{ also } \frac{3\pi}{2}$ .

$$\cos \left[ 2\pi f_c t + \frac{\pi}{2} \right] = \sin (2\pi f_c t) \text{ and } \cos \left[ 2\pi f_c t + \frac{3\pi}{2} \right] = -\sin (2\pi f_c t) \quad (2)$$

This is of high importance due to the fact that cosine and sine waves have been orthogonal signals, indicating that they have been unrelated in the time over symbol duration. Even in the case where their frequencies have been the same, they might be transmitted through same antenna as well as being recovered via same receiver with no mutual interference. In the case when 2 signals have been orthogonal, it has been general for representing them as 2 perpendicular vectors which are forming basis in  $R^2$ . This is resulting in conceptualization regarding modulated symbols as points in the constellation, as can be seen in the Fig. 2.

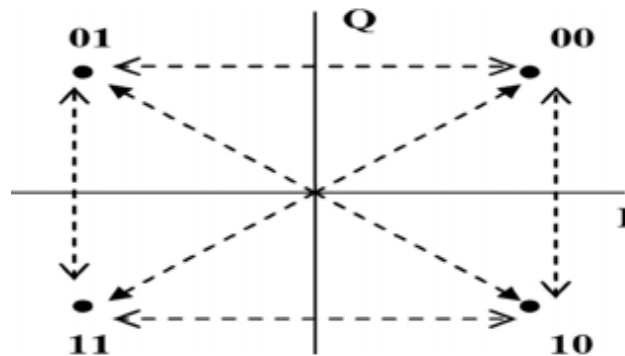


Figure 2: QPSK constellation

## 2) Quadrature Amplitude Modulation (QAM).

This feature is considered as easiest type related to digital modulation involve transmitting sequence of the wave-forms ("symbols")  $s_i(t)$  regarding equal duration  $T$  in which each one of the waveforms has been independently from set of  $M$ . QAM, in the case when utilize for the digital transmission with regard to radio communication applications has the ability of carrying high rates of data in comparison to ordinary amplitude modulated systems, also the phase modulated ones [6]. With regard to PSK, and so on, the number of the points in which signals might rest, for instance, number of points on constellation has been specified in modulation format description, for instance. 16-QAM using 16 point constellation [8]. Whereas utilizing QAM, constellation points have been typically arranged in square grid with the equal vertical as well as horizontal spacing, thus the major general forms of the QAM applying constellation with number of points that are equal to power of 2 i. e. 2, 4, 8, 16 . . . [8]. With the use of high order modulation formats, for instance, more points on constellation, there is a possibility for transmitting more bits for each one of symbol

points have been closer, thus with high susceptibility to noise as well as data errors. This result in conceptualization regarding modulated symbols as points in constellation, as can be seen in the Fig. 3.

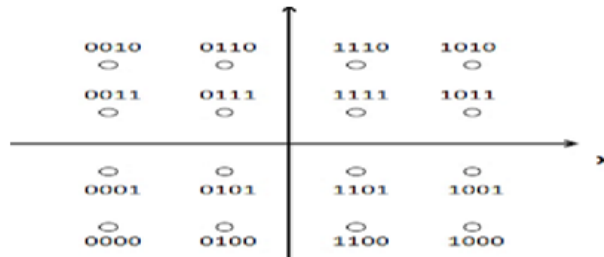


Figure 3: QAM constellation

### 3) Frequency-Shift Keying (FSK).

FSK is considered as a form related to constant-amplitude angle modulations comparable to the standard FM apart from modulating signal has been binary signal which vary between 2 discrete voltage levels instead of continuously modifying the analog waveform. FSK indicates the type related to frequency modulation which is assigning bit values to the discrete frequency levels. FSK has been divided in to coherent and non-coherent forms [9].

- With regard to the FSK's noncoherent forms, instantaneous frequency shifting between 2 discrete values referred to as " mark" as well as "space" frequencies.
- With regard to FSK's coherent forms, there has been no phase discontinuity in output signal. The FSK modulation format generating modulated wave-forms which have been strictly real values, and therefore tending for sharing general features with the quadrature modulation systems.

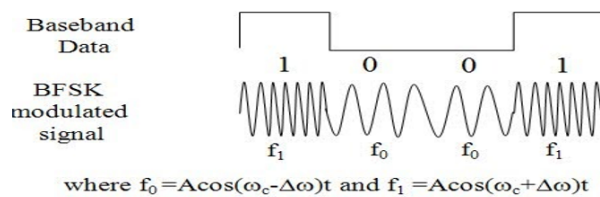


Figure 4: FSK modulation

### B. Communication channel model

The information signals in the systems of communication are suffering from the quality degradation in the case when they have been propagated from transmitters to receivers through communication channel. Also, the transmitted signals have been distorted and attenuated in channel. Signals are losing a few of the energy because of channel impedance, resulting in attenuation [7] . The distortion changing the form and shape of signal. Such condition happens in the case when over one of the signals arriving with various frequencies at the side of receiver and in the case when channel impairments exist.

Random noise is other transmission impairment's source, originating from many natural as well as artificial sources. Such noise type has been specified as random since it is unpredictable, also essential task in studying transmission impairment in the communication systems. The presence regarding such impairments in the signal transmission making it midcult in identifying the type of modulation utilized for transmitting information signal to receiver. Furthermore, the Additive white Gaussian noise (AWGN) has been common channel noise which typically electing signal amplitude. Thus, with the existence of the noise, received signal has been specified as follows: [7] .

$$r(t) = s(t) + n(t) \quad (3)$$

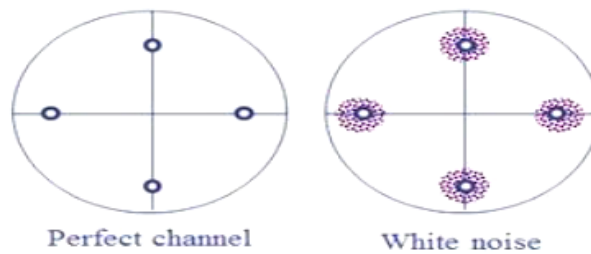


Figure 5: Effect of AWGN on DQPSK modulated channel [7]

### III. MODULATION CLASSIFICATION FEATURES

With regard to the presented section, a few of the identified features developed for modulation classification will be listed. Some studies utilized different features and indicated the results for the MR. Initially, this work will be examining spectral-based features exploiting spectral properties related to various signal components. Wavelet-based characteristics have been provided as other method to the feature-based modulation classification utilizing signal wave-form. High-order statistical characteristics have been studied as optioned to the classifier digital modulations regarding various orders and types. Cyclic characteristics according to cyclostationary analysis have been provided at the end.

#### A. Spectral-based features for modulation classification:

Nandi and Azzouz in 1990 suggested a few of the key signal spectral-based features for classification related to the basic analogue as well as digital modulations (Nandi & Azzouz, 1995). There have been 3 significant parameters in the instantaneous feature extraction: instantaneous frequency, instantaneous phase, and amplitude, that have been specified through  $a_n$ ,  $\phi_{NL}$  , and  $f_N$  . They might be simply acquired in a lot of ways, for example, by Hilbert transform [10].

$$a(t) = \sqrt[2]{r^2(t) + r^2(t)} \quad (4)$$

$$\phi(t) = \tan^{-1} \frac{r^2(t)}{r^2(t)} \quad (5)$$

$$f_N = \frac{1}{2\pi} \frac{d_{quw}(t)}{dt} \quad (6)$$

In which  $r(t)$  has been real valued modulated signal, also  $\check{r}(t)$  has been the Hilbert transform. A lot of spectral characteristics have been utilized for the digital modulation identifications, that have been suggested in the study have been listed in Table I [8] , Past researchers provided many FB methods on frequency and time domains. Table I presenting certain purpose related to each one of the features. Maximum power related to the spectral density (PSD) on the basis of information conveyed via signal envelope, like M-QAM and M-ASK for the digital modulation, also  $\gamma_{MAX}$  value should be non- zero. In the case when modulated signal has constant amplitude, like M-PSK and M-FSK, maximum value should be zero. Thus, max could be utilized for discriminating between M-QAM and M-ASK along with constant amplitude M-FSK as well as M-PSK digital modulation systems [11] [12]. Average value related to max has been utilized for discriminating between Gaussian FSK, Gauss minimum shift keying (GMSK) , and continuous phase FSK [13]. Moreover, a lot of studied utilized such features for discriminating the modulation scheme's order, like M-FSK and M-ASK [14]. The features  $\sigma_{aa}$  as well as features  $\sigma_a$  have been utilized for determining and classifying high order regarding M-QAM and M-ASK, such features have been comparable to the first feature  $\gamma_{MAX}$  [18].  $\sigma_{aa}$  is utilized for classifying between orders of M-ASK.  $\sigma_a$  has been utilized for determining ASK from PSK [12] [14] [15]. The sixth feature  $\sigma_{af}$  has been utilized for classifying high order regarding M-FSK and depending on the variation in the signal frequency [15] , while the second feature  $\sigma_{ap}$  as well as the third feature  $\sigma_{dp}$  have been highlighting the variations in signal instantaneous phase. The second feature  $\sigma_{ap}$  utilized for classifying high order related to the M-PSK, also separating between PSK-4, ASK-4, ASK-2, and, PSK-2, while the third feature  $\sigma_{dp}$  utilized for classifying PSK, ASK-4, and ASK-2 [20]. The eighth Feature  $\mu_{42}^a$  has been utilized for classifying FSK/ PSK from the ASK/ QAM, also the ninth feature utilized for classifying FSK from the PSK [14] [15] [16] . The fourth feature p on the basis of assessment of spectrum symmetry around carrier frequency, for the symmetric modulations as QAM, AM, or ASK, such value has been approximate to 0, yet for the asymmetrical PM or FM modulations it is showing the way that energy has been shifted in frequency spectrum on the basis of transmitted information [17] . Even though that such features can be extracted simply, they have high sensitivity to the noise and might be producing estimation errors. Also, extraction related to the instantaneous information totally depending on on thresholds which must be normally set in advance.

#### B. Statistical-based features for modulation classification:

With regard to such section, the study is focusing on high-order statistics (HoS) -based features, particularly the cumulant-based and the moment-based features, that have been generally utilized for the feature discrimination on the QAM, PSK, and ASK modulation types. The major advantages related to high-order statistics have been robust against phase rotation, the ability for removing noises, also the reflection related to high-order properties regarding the signal [18] [19].

##### 1) High-order moment-based features.

The moment has been typical concept related to probability distribution moment functions. Also, the moment has been an approach for quantitatively evaluating the function's shape. In the year 1986, Hipp provided 3rd-order moment regarding demodulated signal amplitude as a characteristic of the modulation-classification [6]. In the year 1992, Hsue and Soliman provided 3rd-order moment-based modulation classifier to classify the order which is related to

the M-PSK [24] ; they indicated that the moment which is related to phase signal with the white Gauss channel that result in the conclusion which moments have been monotonically increasing function in terms of M-PSK modulations. Therefore, higher-order M-PSK modulations with high moment values, providing condition with regard to classification regarding M-PSK modulations of various orders [20]. The calculation related to kth order moment of signal phase has been specified as can be seen in Equation 7 ,

$$\mu_k(r) = \frac{1}{N} \sum_1^N \varnothing^k(n) \quad (7)$$

In which  $\varnothing(n)$  has been phase regarding  $n^{th}$  signal sample, the signal received as well as  $N$  representing total number of the samples. The Spooner utilized high-order cyclic moments as features (in addition to cyclic moments) with regard to classification of the modulation with the similar cyclic auto- correlation functions (Spooner, 1996). With regard to the presented section, using the next expression to estimated  $k^{th}$  moment regarding complex-valued signal  $r = r[1], r[2], \dots, r[N]$ , 8

$$\mu_{xy}(r) = \frac{1}{N} \sum_1^N r^x [n] \cdot r^{*y} [n] \quad (8)$$

In which  $x + y = k$  and  $r^{*}[n]$  representing complex conjugate of  $r[n]$  [6].

## 2) High-order cumulant-based features.

The (HOCs) have been second statistical features examined following moments. Swami and Sadler in the year 2000 provided fourth-order cumulant related to complex-value signal as features with regard to classifications of M-QAM, M-PSK, and M-PAM modulations. With regard to signal  $r[n]$  , 2nd-order moments might be specified in one of the 2 approaches [Equation 9 and Equation 10].

$$c20 = E r^2(n) \quad (9)$$

$$c21 = E |r(n)|^2 \quad (10)$$

Comparably, fourth-order moments as well as cumulants might be specified in 3 distinctive approaches utilizing various placements related to the conjugation [Equation 12 and Equation 13],

$$c40 = cum(r(n), r(n), r(n), r(n)) \quad (11)$$

$$c41 = cum(r(n), r(n), r(n), r^*(n)) \quad (12)$$

$$c42 = cum(r(n), r(n), r^*(n), r^*(n)) \quad (13)$$

The HOC features have high robustness to the noise, particularly in the case when cumulants high in comparison to second order have been utilized. The HOCs related to demodulated signals have been fairly equal to the ones related to the transmitted signals [21]. Cumulant values might be utilized for modulation discrimination in 2 ways. The initial approach has been through generating the hierarchical schemes which adequately discriminating the type and order of digital modulation (M-QAM, M-FSK, M-ASK, and M-PSK). The second application related to cumulants has been

provided in [22] through comparing the evaluated value to real value. Also, multipath channel impacts could be simply modelled utilizing HOS features [22] , [23], [24], that have high robustness to frequency, timing errors, and phase offset. In a study conducted by [25], extracted features from the ratio as well as absolute related to HOC have been utilized as characteristic parameter to classify between 16-QAM, M-PSK, M-FSK, and M-ASK, and between M-ASK and M-PSK [24].

### 3) Cyclostationary analysis-based features.

The signals have been stationary in the case when their spectral contents and frequency have not been changed in terms of time. This has been because of the fact that when the sine waves have been created with the use of software of function generator, frequency values have been chosen and maintained forever-constant. Therefore, the sine wave's frequency content wont be changing with the time, thus it has been an example with regard to stationary signals. Assume changing frequency, then it is going to be a new sine wave. Also, the stationarity has been linked to the behavior of signal's frequency contents in terms of time and nothing more. The process of cyclostationary has been a signal with statistical properties cyclically varying with time [26]. In the year 1994, Gardner introduced signal cyclostationary analysis, exploiting periodic properties related to cyclostationary process. In the year 1988, Spooner and Gardner initially carried out cyclostationary analysis with regard to modulation classification problems using the differences between cyclic spectrum patterns related to various modulations [6]. In the year 2009, Ram Kumar according to features detection with regard to modulation classification [6]. Also, the cyclo-stationary characteristics or containing second order periodicity in the case when cyclic auto-correlation can be seen in the Equation 14

$$R_x^a = \lim_{n \rightarrow \infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} x(t + \frac{\tau}{2})x(t - \frac{\tau}{2})e^{-i2\Pi a t} dt \quad (14)$$

In which  $x(t)$  representing sinusoidal signal, frequency  $a \neq 0$ , also it isn't identically zero as a function of  $\tau$  .

### 4) Constellation shape features for MR.

Constellation diagram can be defined as representation related to the total number of points as well as the locations, utilized for examining the geometry shape regarding constellation diagram of the modulating signals, like QAM and PSK signals, each one of the locations has certain distance as well as phase in terms of origin point and has been utilized via Mobasseri [27] for transferring phase-amplitude distributions to the 1-D distributions. The modulation classification majorly is considered as noncooperative procedure. Not much is known related to propagation characteristics, baud rate, carrier frequency, symbol timing, and phase. Furthermore, the channel fading might have considerable effect on reconstructed constellation. There have been general approaches for the clock recovery (early-late gate synchronizer) , baud rate recovery (Mth law non-linearity) , also carrier frequency estimation (CPS). All these methods have been accompanied via the errors affecting the constellation shape [27]. With regard to suggested constellation-wavelet transform automatic identifier (C-WT AMI) for identifying the order related to received signal of the QAM as well as the simulation results showing that the suggested system has been of better performance, also it might inerrable in the case when SNR over 4-dB. In a study by [29], intelligent constellation diagram analyzer has been suggested for implementing OSNR and MFR evaluation with the use of CNN-based deep learning approach as well as experimental

results indicating that OSNR estimation errors with regard to all signals have been not more than 0.7 db.

5) Analysis and discussion of modulation classification features.

The spectral-based features are having simple and low complexity with regard to implementations and extracting the features to discriminate between the modulation systems, like M-FSK. Yet, they have high sensitivity to the AWGN. Also, the HOS come with high resistance and not much impact to the additive noise in addition to the multipath fading channels, also more sensitive to discriminate between the modulation systems, like M-QAM and M-PSK. The cyclostationary features come with high resistance to the noise at low SNR, yet with higher complexity, also might not be discriminating large set related to the modulation systems. The FFT features have high robustness at the low SNR as well as more sensitivity to discriminate M-FSK modulation systems. Wavelet feature has been adequate to discriminate modulation approaches at high SNR and requiring various samples. The constellation feature come with more sensitivity to the noise and requiring higher SNR for achieving excellent performance.

*C. Classifier's types utilized for modulation classification*

With regard to the section 3, collection related to signal features for modulation classifications will be listed. The phase following feature extraction in the AMC has been identifying the received signal's type. The presented will be introducing 2 ML-based classifiers, referred to as KNN and SVM, after that, the issue related to the feature space dimension reduction has been discussed via various algorithms involving Linear Regression, ANN, GA, Genetic Programming GP, PCA and LDA, also combinations related to AI approaches, were utilized for the classification. The studies utilized optimization approaches for selecting significant or dominant features from extracted features with regard to enhancing the classifier's recognition accuracy. They were specified AWGN for being a noise related to AMC (due to the simplicity). Yet, some studies specified fading channels in the AMC. Details related to each one of the classifiers offered in the next section.

1) K-nearest neighbor classifier ( KNN) .

KNN has been considered for being slow-adapting, nonparametric, also lazy algorithm in a way that it is not making assumptions on underlying data distributions and requiring further memory and computations. Yet, because of the non-parametricness [30] , KNN has been adequate for real-world issues since a lot of the obtained data not agreeing with the assumptions which are made in theory for the mathematical convenience. This is resembling the SVM's philosophy in which the nonsupport vectors might be eliminated without affecting the performance. Fundamental principles regarding KNN has been the distance between the samples; the first sample has been referred to as trained sample, while the other sample has been test sample. Also, KNN classifier calculating the test sample's distances in terms of class in training sample KNN working with the minimal training step, yet, the testing has been achieved over the entire testing data requiring further memory for the storage [30]. In a study conducted by [31] , the digitally modulated signals, which are referred to as, 64-QAM, MSK, 2-FSK, QPSK, BPSK, 8-PSK, 4-FSK, and 16-QAM, have been specified with the use of KNN Classifier. The GP for new sample data generations with the KNNs as fitness evaluator for improving the efficiency. Accuracy [32] . In a study conducted by [33] there are 4 modulation types have been specified: QAM-64, QPSK, BPSK, and QAM-16. In a study conducted by [34], the Hierarchical Polynomial

( HP) classifier has been suggested for automatically classifying MQAM and MPSK signals in the Additive White Gaussian Noise ( AWGN) besides the slow flat fading environment. Also, the system applies high order cumulants ( HOCs) related to received signal for distinguishing between various types of modulation. The suggested system indicated total improvements in probability regarding correct classifications reaching 100% utilizing just 512 received symbols at 20-dB in comparison to 98% as well as 98.33% in the case of utilizing further complicated systems such as GP-KNN and SVM classifiers.

## 2) Support vector machine (SVM)

SVM is providing other approach for achieving classifications in current multi-dimensional feature spaces. It was used for classification regarding various datasets (Akay, 2009; Polat and Gunes, 2007 ; Mustafavand Doroslovacki, 2004) . Even though that the ANN have been majorly utilized for the AMC, they might be having some drawbacks which might be overcome via SVMs, for instance, the training might be degrading the performance, causing over-fitting and/or local minimum [26] . Also, the SVMs might be solving the overfitting at the low SNR conditions. The approaches utilized for these conditions have been repetitive banded support vector machine (BSVM) or multi-class support vector machine (MSVM) . With regard to the BSVM, the SVM might be utilized for classifying the first class from all classes and after that reused to classify second class from the rest till reaching last class. With regard to the MSVM, high-n dimension feature space has been utilized [35]. In a study conducted by [36] , suggesting novel scheme of AMC via combining SVM and GP for classification of the 16-QAM and 64-QAM signals, the results showing that the SVM assisted GP might be producing excellent performance. In a study conducted by [37] , PSO has been applied for configuring kernel parameter with regard to feature selections as well as digital modulation type classifications to enhance SVM's performance. Results showing that with the infinite SNR, the accuracy will be 99.9%. In a study conducted by [38] , new approach for the automatic modulation classification related to the digital communication signals utilizing SVM on the basis of hybrid features, cyclostationary, in addition to information entropy has been suggested. The results showing that the suggested approach outperforming the current approaches with regard to noise tolerance and classification performance.

## 3) Linear regression

This is considered as an approach extensively utilized in the digital signal processing. With regard to SVM and KNN classifiers, there is requirement for having a lot of features to enhance the accuracy of classification. Yet, the two classifiers are suffering in the case of increasing the number of features. That has been why decreasing feature space dimension has been of high importance. Utilizing ML algorithms, there have been 2 approaches for doing so. Initially, the feature space dimension might be decreased through removing certain features making no or less contributions to classification task. Second, the feature space dimension might be decreased through combining current features into few novel ones [6] . Whereas the feature selection has been efficiency approach for reducing the complexity related to feature-based modulation classifier, eliminating the features might be often destructive [6] . That has been without indicating that often the features have been of high importance in certain degree and feature's elimination might be destructive for classification performance. In such condition, more conservative method has been required

for the dimension reductions. Thus, the feature combination was specified for not only feature dimension's reduction, yet to enhance such feature's performance. It includes finding linear function which is better fitting certain set related to samples [39]. Also, linear function excellently fitting certain set of samples as can be seen in the Fig. 6 coefficients  $a$  as well as  $b$  minimizing MSE:

$$MSE = \sum_{i=0}^{N-1} (d_i - a \cdot i - b)^2 \quad (15)$$

In which  $d_i$  representing  $i^{th}$  input value ( $i \in 1...N$ ),  $a$  representing slope as well as  $b$  value at index 0 related to linear regression function.

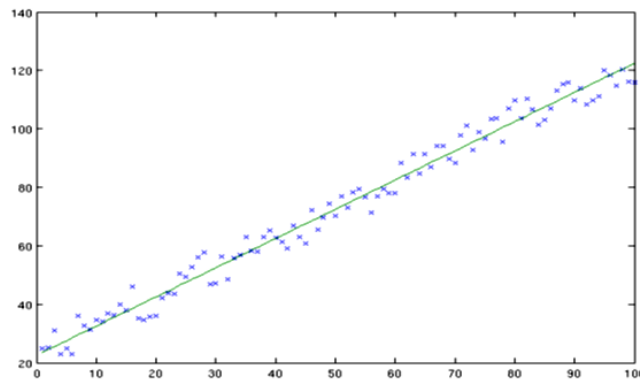


Figure 6: Example related to linear regression function and values from which it has been estimated

There have been 2 tools of logistic regression in the family related to the generalized linear regression methods, referred to as multinomial logistic regression and binomial logistic regression. The logistic regression providing a toll for combination and feature selection. Yet, the multiclass classification has not been always adequate for the linear regression-assisted feature selection as well as combination. Also, it has been often better for dividing classifications into multiple stages.

#### 4) Artificial neural network for feature combination (ANN)

The major properties related to NN have been the capability for learning complex non-linear input-output relationship, using sequential training processes, also adapting to data. The major utilized family of the NNs for the tasks of pattern classification [40], has been feed-forward network, including multi-layer perceptron as well as Radial-Basis Function (RBF) networks. Other major network has been Kohonen-Network or Self-Organizing Map (SOM) [41]. ANN specified as a computing system with a lot of processors on the basis of human's central neural system. The 3 layers of ANN are output, hidden, and input layers [42]. A lot of issues existing in the ANN affecting the performance. ANN come with limited generalization ability at low SNR. In a study conducted by [43], ANN's classification accuracy has been improved for identifying the digital modulation signals at the low SNR. Yet, such approach just covered the low-order digital modulations. In a study conducted by [44], cyclic frequency domain as well as the backpropagation neural network (BPNN) have been utilized as classifier and input attribute. Such approach enhanced the accuracy

at the low SNR, yet requiring significant training. In a study conducted by [45], applied the technique of pattern recognition on the basis of statistical parameters, applying ANN for classifying 5 distinctive digital modulation formats (QPSK, 2-FSK, 2-ASK, 4-ASK, and BPSK). The study is dealing with the automatic recognition related to intra- and inter-classes regarding the digitally modulated signals. The work showing that prompt and accurate modulation recognition has been likely beyond low bound of 5-dB. In a study conducted by [46], constructed characteristic parameters to recognize the signals in cyclic frequency domain, also using 3-layer NN as classifier for identifying modulation mode. The experiment indicating that it might be recognizing 2-ASK, QPSK, 8-FSK, 2-FSK, 4-FSK, BPSK, and MSK in the case when SNR has been high in comparison to 0 dB, recognition rate achieved 95%. In a study conducted by [47], there have been MSK, M-ary QAM, M-ary PSK, M-ary ASK, M-ary FSK, and OOK signals analyzed. Variance, mean value, as well as the central moments up to 5 of the CWT utilized as signal features. PCA has been utilized for reducing the number of the features. Also, multilayer NN which has been trained with the back-propagation learning algorithm has been specified as classifier. In a study conducted by [48], suggesting AMC architecture, the study initially suggesting different statistics serving as features regarding AMC signals; then, designing ANN based classifier performing AMC over variety of SNRs. Also, the study applies Nesterov accelerated adaptive moment (NADAM) estimation approach for improving the classification performance related to ANN. A work of high importance on the deep neural network (DNN)-based AMC has been indicated in [49], that utilized DNN structure with 3 hidden layers. There are 21 characteristics from the data samples which have been fed to classifier. The suggested classifier generated probabilities regarding all modulation classes at each one of the nodes through using Soft Max layer at output layer. The suggested model has been estimated for AMC within AWGN as well as Rican channel environments through specifying Doppler's frequencies in addition to the SNR range. The results indicated that 90% classification precision has been reached. Current enhancement has been using the deep DNN for identifying signals in the fiber-optic networks. The algorithm applied via [50], starting via using constant modulus algorithm (CMA) equalization after that find signals amplitude histograms (AH) as well as feeding data to DNN. Non-data-aided (NDA) modulation format identification (MFI) has been applied to identify the 3 modulation types as well as reaching 100% accuracy over variety of OSNR.

##### 5) Genetic algorithm(GA)

This algorithm has been one of the stochastic optimization algorithms adopting the theory of Darwin (survival of the fittest). The algorithm has been running via iteration related to individual selection, re-productions as well as evaluations. Recently, GA has been indicated in various applications in the sector of engineering, like evolutionary NNs, evolutionary control systems, adaptive filter design, feature extraction, and so on. There are 2 issues in the GA which are genetic coding applied for defining the problem as well as evaluation function. Without them, the GA has just meaningless repetition related to processes. With regard to modulation recognition problem, defining evaluations as recognizer's overall performance, that has been average performance related to the training, testing, and validation. Thus, GA has been utilized for seeking maximum score that has been returned through each one of the individuals [51]. In a study conducted by [52], GA has been applied for optimizing the distance measures utilizing

the sampled distribution parameters with regard to distribution tests between the signals. Also, the final decision has been made on the basis of distances between the tested signal as well as the candidate modulations. The suggested approach has benefits in computational complexity and classification accuracy over the major present classifiers. In a study conducted by [53] the optimization module has been specified as optimizing the recognizer design through GA for selecting optimum features which have been fed to classifier. The suggested approach has extremely elevated recognition accuracy with 6 features chosen via optimizer.

#### 6) Genetic programming (GP)

Koza introduced GP as other advancing ML algorithm (Koza, 1992) . It has been utilized to classify a lot of types related to signals and data (Espejo, Ventura and Herrera, 2010) . Also, a study conducted by Zhu et al. initially applied GP for the modulation classification feature selection as well as combination (Zhu, Nandi, & Aslam, 2010) . In addition to that, the same work extended the applications regarding GP in the modulation classification through combining GP with the other ML algorithms for achieving enhanced classification performances ( Aslam, Zhu and Nandi, 2012; Zhu, Aslam and Nandi, 2011) .

**GP has on other ML approaches have been listed as follows: [6] .**

- No previous information related to statistical distribution of data has been required.
- Data pre-processing has not been needed and data could be directly utilized via GP in the original form.
- GP returning mathematical function as output that might be directly utilized in application environments.
- GP has inherent ability for selecting features as well as ignoring the others.

In a study conducted by [54], suggested novel AMC system through combining GA with SVMs for classifying 16-QAM as well as 64-QAM signals. SVM assisted GP might be producing better accuracy in comparison to certain other approaches.

#### 7) Schemes of linear classification

The schemes of linear classification working via projecting the data into feature space with the use of linear mapping, after that compare the results to centroid for each one of the classes. In the case when the data has been linearly separable, such systems are working well. Such algorithms attempt for finding optimal projection matrix.

- Principal component analysis (PCA)

PCA seeking best data representation in least-squares sense. This is done via de-composing data covariance matrix into the eigenvectors as well as selecting the most important of them for forming projection matrix. Training data in such condition has been matrix  $X$  regarding column vectors, referred to as,  $X_i$  which contain the selected signal statistics. Assuming that there have been total  $P$  of such statistical profiles. Assuming  $N$  representing the number of the classes (types of modulation) specified in training set [55] . Assuming that  $n$  number of the training profiles in each one of the classes, thus  $P = N \cdot n$  [56] . In a study conducted by [47] M-ary ASK, M-ary PSK, M-ary FSK, M-ary QAM, OOK as well as MSK signals analyzed. Mean value, variance in addition to the central moments up to 5 CWTs utilized as signal features. PCA has been utilized for reducing the number of features. Multi-layer NN

trained with the back-propagation learning algorithm has been specified as classifier.

- Linear discriminant analysis (LDA)

PCA is specified as compression system, it is constructing feature space through arbitrarily choosing the major important eigenvectors as the basis vectors. At the same time, LDA seeking various projection matrix  $W$  which is going to be maximizing separation between classes [55]. LDA and PCA working well with classes which have been linearly separable [56]. In a study conducted by [61] modulation classification was implemented with the use of LDA on the fading channels. Also, features utilized for classification have been high order cummulants, also high order cummulants. LDA classifying received signal into set of various classes. The efficiency metrics have been minimum distance criterion discriminating received signal dataset into various classes. In a study conducted by [57] presenting Stock well transform (S-transform) based feature extraction with regard to classification of various digital modulation systems utilizing various classifiers like NN, SVM, LDA, NB, k-NN. Various modulation systems, for instance, MSK, QPSK, BPSK, and FSK utilized for classification. The S-transform based feature outperforming the wavelet transform-based features with more effective classification accuracy, also not much computational complexity. In a study conducted by [58] the modulation classification regarding digitally modulated signals has been achieved utilizing LDA within the impact related to AWGN in addition to channel impact like fading. Modulations specified for classification purposes have been PSK2 to 64, FSK 2 to 64 and QAM2 to 64. The algorithm's performance showing substantial organization regarding various digital modulated signals. Furthermore, the simulation results showing that LDA has higher classification accuracy at low SNR on the AWGN channel in addition to the fading channels that have been specified. Confusion matrix with regard to PSK2 to 64, FSK 2 to 64 and QAM 2 to 64 showing classification efficiency which is related to the suggested algorithm at 10 dB and 0 dB SNR value.

#### 8) Complexity analysis for classifiers

A lot of researches examined the complexity analysis related to classifier utilized with MR in various methods. With regard to ANN classifier in [15], rough sets utilized for chosen features with Neural Network decreased the complexity of network. Combination related to rough sets as well as NN has been small training time. The approach might be removing redundant features from training samples, also simplifying the structures related to ANN classifier. In a study conducted by [44], features sub-set selection utilizing PCA has been utilized for reducing the complexity regarding utilized NN via selecting best features. In a study conducted by [59] [57] [58], feature sub-set selection utilizing LDA within the impact of the AWGN in addition to channel impact like fading has been utilized for reducing the complexity as well as selection of best features. Comparably, in the SVM classifier, a few of studied have been decreasing the complexity. In a study conducted by [25], some features extracted from data-set include twenty-seven features, thus, the complexity related to computation as well as runtime is going to be elevated. Thus, feature sub-set selection has been required for reducing SVM complexity via using PSO [37]. Decreasing the complexity in the k-NN approaches is of high interest to certain studies. In a study conducted by [32], GP generated super features from dataset on the basis of single-stage strategy resulting in decrease of computational time. In a study conducted by [60], the study compared KNN classifier to the other classifiers, like ANN and SVM, also indicated that KNN

has not much computational complexity in comparison to ANN and SVM.

#### *D. Performance analysis*

Comparing and studying some modulation classifiers isn't complicated or simple task. Studies have been developing various algorithms and approaches with regard to automatic modulation classifier within various channel signals as well as conditions. Therefore, the performance related to various classifiers might not be put to comparison in the case when modulation scheme has been distinctive. Also, feature set utilized through each one of the systems should be indicated for achieving dependable and unbiased comparison. Table II presenting comprehensive and lucid comparison related to different works on the AMC with the key features as input and SNR as well as accuracy as output parameters. Studies have utilized different methods with regard to feature selection, classifier types, in addition to the modulation set, also estimating their suggested approaches within different SNRs. There are 4 major conclusions might be obtained in the following way:

- 1) Choosing adequate features might be enhancing the robustness of modulation classifier toward noise, also might be having high sensitivity with regard to differentiating non-linear and linear modulation, thus enhancing the system's performance.
- 2) Decreasing the feature's complexity (spectral features, high order statistical, and so on) might be enhancing the performance classifier.
- 3) Decreasing the classifier's complexity (KNN, PCA, ANN, SVM, DT, LDA, and so on. ) , also the running time could be enhancing the performance classifier.
- 4) Discrimination has been complicated in the case when order modulation types increasing.
- 5) Recognition has been complicated in the case when high order modulation types and order utilized for high order QAM at low SNR like (128 QAM,256 QAM, etc. ) .

#### *E. Weakness and strength facts*

AMR in the receiver end not just recognizes the modulation scheme, but it efficaciously demodulates a signal. Systems typically accept a modulated signal which effected by noise and attenuation owing to channel losses. Interference is existing as a result of cross channel effect, creating the task challenging and cumbersome. Information signals in communication systems endure from quality degradation as propagated from the sender to a receiver through a communicating medium. The sent signals are attenuated and distorted in the channel. The signal loses several of its energy because of channel impedance, producing attenuation. Distortion alters the form or arrangement of the signal. The presence of these impairments and conditions in signal transmission creates it hard to classify the modulation type employed for sending the information signal to another side. Numerous digital signals impose innumerable characteristics should be defined for recognizing the signals. Consequently, like these characteristics are sensitive to digital modulation schemes and insensitive to noisy channels and SNR differences should be selected. No difficult and fast rule is found for feature selection. Scholars have used numerous features and testified their outcome for MR. The selected features, which are used in the literature for discriminating the modulation categories, must be further sensitive in terms of discrimination and insensitive to noisy channels and SNR variations with less computational complication. The complexity of ML rises and leads to performance

degradation as huge data sets and complex features have employed for recognition. ML can't be adopted in real-time environments. SVM and KNN classifiers can produce higher classification rates as compared with ANNs. KNN classifiers have been favorite for the reason that they are less complex than SVMs. The DT performance is lower as compared with ANN, SVM, and KNN. Nevertheless, DT has been simpler for design and implementation and can classify an extensive range of modulation systems through addition of several decision points without classifier retraining.

TABLE I  
 SPECTRAL FEATURES APPLIED FOR THE MODULATION CLASSIFICATION [6]

No.	Feature	Mathematical Equations
First feature	maximal value related to spectral power density instantaneous amplitude of received signal $\gamma_{MAX}$	$\gamma_{MAX} = \frac{MAX DFT(A_{CN}) ^2}{N}$ In which DFT (-) has been DFT, $A_{CN}$ has been normalized as well as centered instantaneous amplitude of received signal, and $N$ representing the number signal samples
Second feature	standard deviation regarding absolute value of on-linear component of the instantaneous phase $\sigma$	$\sigma_{ap} = \sqrt{\frac{1}{N_c} \left( \sum_{A_n[n] > A_t} \Phi_{NL}^2[n] \right) - \left( \frac{1}{N_c} \sum_{A_n[n] > A_t}  \phi_{NL}^1[n]  \right)^2}$ where $N_c$ representing the number of samples meeting the condition: $A_n[n] > A_t$ . The variable $A_t$ representing threshold value filtering out low-amplitude signal samples due to high sensitivity to noise. Term $\phi_{NL}[n]$ denoting non-linear component of instantaneous phase related to $n$ th signal sample.
Third feature	standard deviation regarding nonlinear component of direct instantaneous phase $\sigma_{ap}$	$\sigma_{ap} = \sqrt{\frac{1}{N_c} \left( \sum_{A_n[n] > A_t} \Phi_{NL}^2[n] \right) - \left( \frac{1}{N_c} \sum_{A_n[n] > A_t} \phi_{NL}^1[n] \right)^2}$ In which all parameters remaining same as in expression for $\sigma_{dp}$ Yet, it has been indicated that absolute operation on non-linear component regarding instantaneous phase has been eliminated.
Fourth feature	spectrum symmetry evaluation around carrier frequency $P$	$P = \frac{P_L - P_U}{P_L + P_U}$
Fifth feature	standard deviation of absolute value of normalized in addition to the centered instantaneous amplitude of signal samples $\sigma_{aa}$	$\sigma_{aa} = \sqrt{\frac{1}{N} \left( \sum_{n=1}^N A_{CN}^2[n] \right) - \left( \frac{1}{N}  A_{CN}^2[n]  \right)^2}$
Sixth feature	standard deviation regarding absolute value of normalized as well as centered instantaneous frequency $\sigma_{af}$	$\sigma_{af} = \sqrt{\frac{1}{N_c} \left( \sum_{A_n[n] > A_t} f_N^2[n] \right) - \left( \frac{1}{N_c} \sum_{A_n[n] > A_t}  f_N^1[n]  \right)^2}$ In which centered instantaneous frequency $f_m$ has been normalized through sampling frequency $f_s$ in a way that equation: $f_N[n] = \frac{f_m[n]}{f_s}$
Seventh feature	standard deviation of normalized as well as centered instantaneous amplitude $\sigma_a$	$\sigma_a = \sqrt{\frac{1}{N_c} \left( \sum_{A_n[n] > A_t} a_{cn}^2[n] \right) - \left( \frac{1}{N_c} \sum_{A_n[n] > A_t}  a_{cn}^1[n]  \right)^2}$
Eighth feature	kurtosis regarding normalized as well as centered instantaneous amplitude $\mu_{42}^a$	$\mu_{42}^a = \frac{E\{A_{cn}^4[n]\}}{\{E\{A_{cn}^2[n]\}\}^2}$
Ninth feature	kurtosis regarding normalized as well as centered instantaneous amplitude $\mu_{42}^F$	$\mu_{42}^F = \frac{E\{F_N^4[n]\}}{\{E\{F_N^2[n]\}\}^2}$

TABLE II  
 REVIEW OF RELATED WORKS FOR STATISTICAL-BASED FEATURES FOR MODULATION CLASSIFICATION

Author (s)	Features	Classifier	SNR	Modulation Chemes	Accuracy
[61] Sept. 2014	Cyclostationary feature	Genetic algorithm + SVM	0-19dB	PSK, QAM ,PAM	98.9 %
[62] June. 2013	MoM based	(ALRT)	0-5dB	16-QAM, 32-QAM 64-QAM	88 %
[63] 2012	Fourth order cumulants	FLOS  likelihood ratio test	-5-20dB	BPSK, QPSK, 16-QAM, 32-QAM	90 %
[64] 2013	time offset, phase shift, amplitude	HLRT-based algorithm	0-20dB	BPSK, QPSK, 8-PSK, 16-QAM, and 64-QAM	
[65] July 6-9, 2015	Constellation	IADA LRBM	-5-15dB	BPSK, QPSK , 8-PSK, 16-QAM	
[57] 2015	higher order cummulants, spectral feature	Multilayer perceptron LDA HMM Gabor filter network SVM	10 dB	PAM, QAM, PSK, FSK	100 %
[66] September. 2019	High-order statistical cyclic spectrum	DL-based methods	0-10dB	MFSK, MPSK, MAPSK, MQAM	90 %
[54] June. 2014	High order cumulants	GP SVM	10-20 dB	16-QAM 64-QAM	90.3 %
[67] June. 2016	amplitude, phase, frequency	DT	10dB	2 ASK, 4ASK, 8 ASK, 2 FSK, 4FSK, 8 FSK, 2 PSK, 4PSK , 8 PSK	
[60] December 2014	Cyclostationarity	KNN	10dB	BPSK, QPSK, FSK,MSK	
[18] February 2014	Spectral-based, Statistical wavelet-based	SVM PSO	6, 9, 16dB	FSK, PSK, ASK QAM/ ASKPSK	96 %
[43] 2014	Statistical parameters	Artificial Neural Network	5 dB	2ASK, 4ASK, 2FSK, BPSK , QPSK	99.0 %
[68] 16 March 2017	Cyclic Frequency Domain	Neural Network	0 dB	2FSK, 4FSK, 8FSK, BPSK, QPSK, MSK, 2ASK	95 %
[47] 2016	The mean value, variance, continuous wavelet transform (CWT)	PCA ANN	0-20dB	M-ASK, MPSK, MFSK, MQAM, OOK , MSK	
[69] November 17, 2014	—————	PCA ANN	—————	AM FM FSK	96.3%
[38] 30 July 2019	hybrid features, cyclostationary, information entropy	SVM	-5,-4-20dB	BPSK, QPSK, 2FSK, 4FSK, MSK	85.92%
[70] 2016	HOC	KNN	0, 5, 10 dB	BPSK , QPSK, QAM 16-QAM,64-QAM	99.57%
[71] 2018	Higher Order Statistic	deep learning architecture	-4, -2, 0, 2, 4, 6, 8, 10, 12 dB	QPSK, 8PSK, 16QAM, 64QAM	Improve 5 % 26 %
[72] 2018	Fractal theory	neural network KNN Random forest	10 dB	MASK, MFSK, BPSK, 16QAM	96 %
[20] 2017	Fractal theory	Gray Relation	-10 dB	AM, FM, PM, ASK, FSK and PSK	94 %

#### IV. CONCLUSIONS

This review paper delivers complete analysis of automatic modulation classification techniques mainly based on feature-based (FB) approach. likelihood approach yields reasonable performances, the computational complication making them unworkable. Also, the likelihood method has been difficult in defining the adequate analytical answer with regard to decision

functions, especially when big unknown parameters. For example, the ALRT wanting the multi-dimensional integrations as well as GLRT requiring the multi-dimensional maximization. Therefore, a lot of unknown quantities as well as prerequisite related to known PDFs making ALRT adequate for the real-world applications. Extension related to the unknown data might be causing comparable LF values as well as incorrect classifications. This study is exploring many features used in the distinctive many modulation types and specifying the usage as well as applicability with regard to exact modulation variants. The instantaneous features have less computational difficulty, yet have been sensitive to noise. Thus, such features must be shared with the other features for developing the performance to classify the signals. Furthermore, this study is discussing classifiers utilized for the AMC thoroughly. KNN, SVM, ANN, GA, GP, linear classification like (LDA and PCA) as well as hybrid algorithms on the basis of such classifiers have been provided. KNN has been estimated for being simple classifiers, SVMs and NNs have enhanced the efficiency of the classification and have more robustness to the noise, yet they have been computationally difficult. PCA or LDA utilized for reducing the dimensions, also PCA and ANN have improved classification performance.

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