An Overview of Feature-Based Methods for Digital Modulation Classification

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An Overview of Feature-Based Methods for Digital Modulation Classification

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Abstract— **This paper presents an overview of feature-based (FB) methods developed for Automatic classification of digital modulations. Only the most well-known features and classifiers are considered, categorized, and defined. The features include instantaneous time domain (ITD) parameters, Fourier transform (FT), wavelet transform (WT), higher order moments (HOM) to name a few. The classifiers are artificial neural networks (ANN), support vector machines (SVMs), and decision tree (DT). We also highlight the advantages and disadvantages of each technique in classifying a certain modulation scheme. The objective of this work is to assist newcomers to the field to choose suitable algorithms for intended applications. Furthermore, this work is expected to help in determining the limitations associated with the available FB automatic modulation classification (AMC) methods.**

Keywords-component; Automatic Modulation Classification; Temporal Time Domain Features; Statistical features; Pattern Recognition;

I. INTRODUCTION

AMC has the role to detect an unknown modulation scheme of a received signal; hence the signal can be demodulated and its information content can be retrieved [1]. An obvious use of AMC algorithms is in military intelligence, where the objective is to decode the message information and search for a specific signal of interest. Furthermore, these types of algorithms also find use in communication jammers, where detection of the modulation type allows generation of energy efficient jamming signals. In adaptive modulation based communication systems, AMC can be used to detect the modulation type at the receiver. Also generic receivers can be designed such that there would be one receiver design for many types of transmitters.

Generally, there are two methods for AMC: Maximum Likelihood (ML) [2][3] and FB methods [4]. Although the ML can lead to optimal solutions, it suffers from high computations. On the other hand, a properly designed FB method can show performance close to the ML with much reduced computational complexity. Due to its low computational cost coupled with its near optimal performance, FB approach is considered in this paper.

Many types of features have been used in AMC, e.g., instantaneous amplitude, phase, and frequency [5]-[8], Fourier [9][11] and wavelet transforms [12][13][18], higher order moments and higher order cumulants (HOCs) [5][9][19][13][20] and cyclo-stationarity [22][25]. Similarly, several types of pattern recognition (PR) methods have been employed for AMC. PR methods include artificial neural networks [15][26]-[28], clustering, support vector machines [12][5][19][13][20][21], decision tree [29], etc. All types of combinations of features and PR methods are possible, and many of those exist in the literature. Their performance, however, might not be easily compared as different algorithms consider different modulation sets and different assumptions; e.g. the presence/absence of pulse shaping filters, channel fading, and frequency carrier and phase offsets.

The objective of this paper is to present a compact overview of available features and classifiers used in AMC. This will assist designers to choose the appropriate algorithms that suite their intended applications. Furthermore, this work is expected to help newcomers to the field to determine the limitations associated with the available FB AMC methods and to pave the road for the development of new AMC designs.

The paper is organized as follows. In Section II, signal models and samples of their features are presented. In Section III, FB AMC algorithms are reviewed. Concluding remarks are given in Section IV.

II. SIGNAL MODEL IN AMC

The general form of received modulated signal is given by [1]

$$r(t) = Re\{\alpha\, e^{j2\pi\varphi}\, e^{j2\pi\Delta f t}\, C(t) e^{j2\pi f_c (t-t_0)}\} + n(t) \qquad (1)$$

where $C(t)$ is the complex envelope of the modulated signal, $n(t)$ is a band limited noise, f_c is the carrier frequency, α is the channel amplitude, φ is the phase offset, Δf is the carrier frequency offset, and $Re\{.\}$ denotes the real part. The complex envelope is characterized by the constellation points C_i and pulse shaping function p(t). For N symbols with periodicity T, the general form of the complex envelope can be expressed as

$$C(t) = \sum_{i=1}^{N} C_i\, p(t - iT) \qquad (2)$$

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The constellation points of digital modulation of order M considered in this paper are given in [30].

III. FEATURES

Most commonly used AMC features can be categorized into five types: instantaneous time domain, transform domain, statistical, constellation shape, and zero-crossing features. Instantaneous features are related to the instantaneous amplitude, phase, and frequency as they represent all variations in the modulated signals. Transform domain features are often extracted by transforming the signal to Fourier and/or Wavelet domains with different pre and post processing operations such as smoothing, normalization, and median filtering. Statistical features make use of HOMs, HOCs, higher order cyclic cumulants (HOCCs), and cyclo-stationarity. The constellation shape features are extracted by different techniques such as counting the number of levels of constellation points, or by comparing a reference of constellation points with that of intercepted signal.

A. Instantaneous Time Domain features

Modulation is characterized by varying the following parameters: carrier frequency, phase, or amplitudes. The instantaneous variation of these parameters is often exploited for the purpose of modulation classification [1][5][14]. Given the Hilbert transformation $\hat{r}(t)$ of intercepted signal $r(t)$ defined in (1), the mathematical formulas for the instantaneous amplitude $a(t)$, phase φ, and frequency f_N are

$$a(t) = |z(t)| = \sqrt{r^2(t) + \hat{r}^2(t)}\,, \tag{3}$$

$$\varphi(t) = \text{unwrap}\left(\text{angle}\left(z(t)\right)\right) - 2\pi t f_c t \tag{4}$$

$$f_N = \frac{1}{2\pi}\,\frac{d(\arg(z(t)))}{dt} \tag{5}$$

Based on the above parameters, several TTD features have been proposed in the literature and are defined in Table 1.

Table 1: Mathematical formula for TTD features.

Feature	Mathematical formula
The standard deviation of the absolute value of the normalized- centered instantaneous amplitude of a signal segment	$\sigma_{aa} = \sqrt{\frac{1}{N_s}\left[\sum_{i=1}^{N_s} a_{cn}^2(i)\right] - \left[\frac{1}{N_s}\sum_{i=1}^{N_s}\lvert a_{cn}(i)\rvert\right]^2}$ Where , $a_{cn}(i) = \frac{a(i)}{m_a} - 1$ and m_a is the sample mean of $a(i)$.
The standard deviation of the absolute value of the normalized-centered instantaneous amplitude in the non-weak segment of a signal	$\sigma_a = \sqrt{\frac{1}{L}\left[\sum_{a(i)>t_{th}} a_{cn}^2(i)\right] - \left[\frac{1}{L}\sum_{a(i)>t_{th}} a_{cn}(i)\right]^2}$ where t_{th} the threshold value of the non-weak is signal in and L is the length of non-weak values.
The standard deviation of the centered non-linear component of the direct (not absolute) instantaneous phase in non-weak segment	$\sigma_{dp} = \sqrt{\frac{1}{L}\left[\sum_{a(i)>t_{th}} \varphi_{NL}^2(i)\right] + \left[\frac{1}{L}\sum_{a(i)>t_{th}} \varphi_{NL}^2(i)\right]^2}$
The standard deviation of the centered non-linear component of the absolute instantaneous phase in a non-weak segment	$\sigma_{ap} = \sqrt{\frac{1}{L}\left[\sum_{a(i)>t_{th}} \varphi_{NL}^2(i)\right] + \left[\frac{1}{L}\sum_{a(i)>t_{th}} \lvert\varphi_{NL}^2(i)\rvert\right]^2}$
The standard deviation of the absolute value of the normalized- centered instantaneous frequency of a signal segment	$\sigma_{af} = \sqrt{\frac{1}{N_s}\left[\sum_{i=1}^{N_s} f_N^2(i)\right] + \left[\frac{1}{N_s}\sum_{i=1}^{N_s}\lvert f_N(i)\rvert\right]^2}$
The standard deviation of the absolute value of the normalized- centered instantaneous frequency of a non-weak segment	$\sigma_{nf} = \sqrt{\frac{1}{L}\left[\sum_{a(i)>t_{th}} f_N^2(i)\right] + \left[\frac{1}{L}\sum_{a(i)>t_{th}} \lvert f_N^2(i)\rvert\right]^2}$
The kurtosis of the normalized instantaneous amplitude μ_{42}^a and frequency μ_{42}^f	$\mu_{42}^a = \frac{E\{a_{cn}^4(i)\}}{\{E(a_{cn}^2(i))\}}$ $\mu_{42}^f = \frac{E\{f_N^4(i)\}}{\{E(f_N^2(i))\}}$
Spectrum symmetry measured by the ratio S given by	$S = \frac{S_L - S_U}{S_L - S_U}$ where, $S_L = \sum_{i=1}^{f_{cn}}\lvert R(i)\rvert^2$ $S_L = \sum_{i=1}^{f_{cn}}\lvert R(i + f_{cn} + 1)\rvert^2$ $f_{cn} = \frac{f_c\,N_s}{f_s} - 1$ $R(i) = \text{FFT}[r(i)]$

Both σ_{aa} and σ_a capture the variation of modulated signal amplitude. Hence, they are used for determining ASK order [29][31][32], and to distinguish ASK signals from PSK signals [24]. Also these features have been used with other features to classify a set of digital modulation schemes [1][33][26]. The instantaneous features related to phase variation is very useful in finding PSK modulation order [31][14], to distinguish MFSK/2PSK from 4PSK/MQAM/MQAM modulations [24], and to separate MASK from MPSK/MQAM. Further, both features can be used in the classification of analogue and digital modulations [1]. With PR classifiers, many AMC algorithms have considered using σ_{dp} and σ_{ap} as input features to ANNs [1] and SVMs [5].

σ_{af} and σ_{nf} are used to find the order of FSK modulation, and to separate PSK signals from FSK signals [24]. Both features have been the subject of study with PR classifiers [1][5]. In [1], μ_{42}^a was used with DT classifier to separate AM from 2ASK/4ASK, and μ_{42}^f to separate FM from 2FSK/4FSK. Further μ_{42}^a has been used to separate FSK/PSK from ASK/QAM [14][24], and μ_{42}^f to separate FSK from PSK [14]. Additional works have shown the use of both features with PR techniques for the classification of several ASK, FSK, and analogue modulation schemes [1][5].

The spectrum symmetry has been used in [1] along with DT and ANNs classifiers to separate VSB from AM/MASK, and to separate LSB/USB from FM/MFSK/DSB/MPSK, and to separate USB from LSB.

Although instantaneous features are easy to extract, they have the disadvantage of being sensitive to noise and have estimation errors. Therefore, these features are often used with PR techniques to improve classification rate at low SNR. Previously, these features were also coupled with the statistical [1] and transformation based features [26].

B. Transformation Based Features

1) Fourier Transform

- The Maximum Value of Power Spectral Density (PSD) of Normalized-Centered Instantaneous Amplitude.

$$\gamma_{max} = \frac{\max|\mathrm{DFT}(a_{cn}(\mathrm{n}))|^2}{N_s} \tag{2}$$

γ_{max} represents the variations in amplitude, which makes this feature useful to discriminate between amplitude and non-amplitude modulations in both analogue [12][29] and digital modulations [1][24]. Using predetermined threshold, this feature is used to discriminate between different types of AM and CW/FM signals [29]. In digital modulation, this feature is widely used to discriminate between MQAM/MASK and FSK/PSK modulations [1][14][24]. γ_{max} is also employed with ANNs [1], and SVMs [12] for classification of various modulation types with different orders.

- The Maximum Value of Discrete FT (DFT) magnitude of The k^{th} power of Analytic form of received signal defined as

$$\Gamma_k = \frac{\max|\mathrm{DFT}(a(i)^k)|^2}{N_s} \tag{3}$$

Γ_k with $k = 2$ and $k = 4$ is used for classification of PSK signals as it is robust with respect to both the carrier frequency offset (CFO) and time offset (TO) [30].

- Signal spectrogram

Spectrogram is a representation that shows spectral density variation with time [11]. This signal representation is generated by FT after dividing the signal into narrow bands. Because this representation reflects the variation of modulated signal parameters, it has been proposed to classify a couple of digital modulations. Two features are extracted from spectrogram image: moments-like features and principle components analysis (PCA) for classification of (PSK/QAM), 2FSK, 4FSK, ASK, and OFDM (8 tones, and 16 tones) [9]. Classification using spectrogram has shown robustness against CFO.

2) Wavelet Transform (WT)

Wavelet transform is another common technique used for features extraction as it has the advantage of being able to reduce effect of noise [9][12][13][29][31][23]. The features extracted from the WT contain time domain as well as frequency domain information, and therefore are more robust with respect to modulation classification than those based on FT. In continuous wavelet transform (CWT), there are some pre and post processing steps to extract features such as, median filtering for outliers removal [9][5][23], mean, variance, and kurtosis of coefficients [23].

In digital wavelet transform (DWT), the intercepted signal is divided into different levels of wavelet decomposition. The first step of the decomposition is achieved by filtering the original signal into two bands, which represents the first level decomposition. The second level decomposition is associated with dividing the lower band of the first level into two bands as in the first step. Repeating this step several times increases the resolution in frequency domain. The DWT based features have been proposed with ANNs [31][23] and SVMs [12] for the classification of different digital modulation schemes including FSK, PSK, and QAM modulations.

C. Statistical Features

1) Higher order Statistics

Higher Order Statistics (HOS) are divided into HOMs and HOCs, which are widely used in classification of various ASK, PSK, and QAM signals as reported in [5][23]. These features have three main advantages: 1) reflect the higher order statistical characteristics of signal, 2) eliminate the effect of noise, and 3) have robustness to phase rotation. For a received signal $x(n)$, a particular HOM, $M_{p+q,p}$, is defined as

$$M_{p+q,p} = E[x(n)^p\ (x(n)^*)^q] \tag{4}$$

HOC is derived from a combination of two or more of HOMs as in C_{42}, which is given by

$$\begin{aligned} C_{42} &= \mathrm{cum}[x(n)\ x(n)\ x(n)\ x(n)^*] \\ &= M_{41} - 3\ M_{20}\ M_{21} \end{aligned} \tag{5}$$

The HOCs features have been used in a number of published works with both DT and PR classifiers as in [1][33][9][5][19][29][13][20][41]. Other features extracted from ratios of HOCs and their absolute values are presented in [19][17][24]. In [33], a hyperspace of HOC is created to discriminate between different modulations. In [29], subspace decomposition was used to select the most efficient HOS features representing MPSK, MASK, and 8QAM. In [21], HOCs are additionally used to estimate and mitigate the effect of multipath. As a result classification performance is enhanced in PSK and QAM modulations.

2) Cyclostationarity (CC)

A random signal is considered cyclostationary if its HOMs are periodic. The signal x(t) is said to be second order cyclostationary at frequency 1/T, if its autocorrelation function satisfies the following equation:

$$\begin{aligned} R_x(t,\tau) &= E\left[x\left(t + {}^{\tau}/_{2}\right) x\left(t - {}^{\tau}/_{2}\right)\right] \\ &= R_x(t + T, \tau) \end{aligned} \tag{6}$$

The cyclostationarity of modulated signal is due to the periodical repetition invoked by the symbol rate. This feature does not need a prior knowledge of CFO, carrier phase offset

(CPO), or TO. Hence, it has been proposed to construct a blind AMC [34][35]. However, robust cyclic frequency estimation can further enhance the classification that is based on cyclostationarity features.

3) Signal Autocorrelation Function

The autocorrelation of OFDM or generally multicarrier modulated signal r_{ss} is given by

$$r_{xx}(m) = E[s(k)\, s(k+m)] = \begin{cases} \sigma_s^2 + \sigma_n^2 & m = 0 \\ \sigma_s^2\, P\{k = I\} & m = N_s \\ 0 & \text{elsewhere} \end{cases} \quad (7)$$

where σ_s, σ_n, I, and N_s are signal variance, noise variance, and cyclic extension, and symbol duration, respectively. In [23], the classification of multi-carrier modulations including IEEE 802.11g, DVT-T, HIPERLAN, ADSL-32, ADSL-32,ADSL-256, VDSL-256,VDSL-1024, and PLC have been considered. The classification is performed by comparing the estimated symbol duration and cyclic extension with theoretical values of each standard.

D. Constellation Shape Features

The geometric shape of constellation diagrams of PSK and QAM signals characterize each modulation scheme. This characterization is associated with number of points and their locations. Each location has a special distance from origin and a special phase. Constellation rotation is used in [28] to transform the phase-amplitude distribution to a one-dimensional distribution. In [36], an AMC has been proposed by comparing a reference of modulation points and intercepted constellation shape. This study has investigated the effect of noise, CFO, and CPO on classification rate. In other works, number of sets of equal amplitude, and Euclidean distances between constellation points have been proposed for classifying various PSK and QAM modulations [36].

E. Zero-crossing (ZC)

Counting the number of zero-crossing of an intercepted signal has been employed for modulation classification with various post-processing steps and likelihood tests for decision making [37][38]. Obviously, the rate of zero-crossing of a PSK signal is fixed for all symbols, while it varies in FSK signals. This feature has been used for determining the modulation order of FSK signals and to discriminate between FSK and PSK modulations [39].

IV. CLASSIFIERS

A natural step after feature extraction is making decision to identify the type of intercepted signal. In FB methods, decision-making can be achieved by two methods. The first is the DT method [1][29][31][14][32], while the second method is based on using PR such as ANNs [1][23][16][36], SVMs [12][5][13][42], or combinations of more than one Artificial Intelligence (AI) technique to optimize the solution [23]. The main objective of using PR techniques is to enhance the classification rate at low SNR [1][19].

Other classifiers include the K-nearest neighborhood with genetic programming (GP) [8], where the GP is used to select the best features from a set of HOCs features. This approach is used to classify 2PSK, QPSK, 16QAM, and 64QAM modulations. In what follows, the focus will be dedicated to the most commonly used PR classifiers, ANNs, SVMs, and DT.

A. Artificial Neural Networks

One of the most popular techniques used in AMC is the ANNs. This technique is very useful when applied to classification problems because it has a flexible structure that makes it easy to implement. In addition, the ANNs can adapt and learn to work with complicated signals [40]. In view of learning algorithms, the ANNs can be categorized into supervised or unsupervised networks. In the supervised ANNs, one part of the data set is used for learning and the other part is used for testing. On the other hand, the unsupervised ANNs cluster the input data and train themselves. The first technique gives results that are more accurate. However, it needs a large number of data compared to the unsupervised techniques. Most of the ANNs that have been tested in AMC field use the supervised learning techniques including Multi-Layer Perceptrons (MLP) and Radial Basis Function (RBF). The Self Organizing Map (SOM) neural network is an unsupervised ANNs technique that has been used in designing AMC.

The MLP is attractive for the designers because it needs small memory. Most of the works used single MLP ANNs as in [33], while others have suggested three cascaded MLP ANNs [1]. The last technique uses the output of the first or second ANNs as an input to the second or third ANNs. The use of MLP gives performance better than DT considering the same features [1]. The other supervised ANNs algorithms being employed in AMC are RBFNNs, which have faster training rates compared to MLP ANNs. Excluding the competence of RBF, there is no significant change in the classification performance using RBFNNs compared to MLPNNs.

SOM NNs has the advantage of being able to determine network structure, as it adaptively selects the suitable number of neurons in the ANNs and needs no earlier knowledge about number of clusters [26][20][16]. A comparison between SOM and MLP for AMC is available in [26], where the SOM shows higher classification rate at high SNR.

An investigation pertaining to the employment of discrete wavelet adaptive network based fuzzy inference system (DWANFIS) in AMC is presented in [27]. When compared with DWNNs, DWANFIS gives a higher classification rate. The work is tested against the classification of CW, 2ASK, 2FSK, 2PSK, and 8QAM modulations. In [20], Genetic Algorithm (GA) has been used in the process of selecting features from TTD and HOCs features that are fed to MLP ANNs classifier.

B. Support Vector Machines

Although the ANNs are widely used with AMC, limitations in training may degrade their performance such as ending up with over fitting and/or local minimum. These limitations are overcome by using SVMs. Further, SVMs provide more generality at lower SNR. The main principle of SVMs is to find the maximum separation between two classes [41]. The non-linearly separable features can be separated by using a specific kernel function that maps the features from input domain to feature domain. In more than two classes of classification problems, binary SVM (BSVM) is used. In this technique, the classification algorithm starts to use the first SVM to classify the first class against all of the others. Afterwards, it constructs another SVM in order to classify the second class against the rest of the classes and so on. Another way to solve multi-class classification problems is by using Multi-class SVM (MSVM), which uses higher dimension feature spaces. In this paper, we outline the previous studies related to the use of SVM in AMC according to the employed features and kernel functions.

Two main SVM structures are proposed in a number of available literatures including BSVM [19] and MSVM such as directed acyclic graphic SVM (DACSVM) [12][5][13]. Generally, SVMs are designed using different kernels such as RBF [12][5][42] and polynomial functions [12][5].

SVMs have shown to achieve higher classification rate than DT and ANNs [5][42] because they do not suffer from the generality problem associated with ANNs and also are not restricted to linearity condition required in selecting thresholds as in DT approaches. Therefore even simple features can yield excellent results when used with SVM. In [9], only the amplitude and phase of the input signal used in an SVM for classification of BPSK, ASK, 8PSK, and 16QAM modulations. This method is able to outperform two likelihood based approaches. Attempts to use GA to optimize the selection of kernel parameters of Wavelet SVM have been reported in [15]. The study has investigated the classification of MASK, MPSK, and MFSK modulations. Although this approach has helped to optimize the classifier parameters, no significant change with respect to the classification rate has been observed.

C. Decision Tree Approach

The DT approach is based on the idea of selecting specific thresholds to separate between modulation types and modulation orders; see [1][29][31][14][32]. The main advantage of using DT algorithms is the simplicity of implementation [39][24]. In addition, DT methods can be promoted to accommodate more modulations by adding additional decision branches. Table 2 provides compact summary of all previously discussed methods.

Table 2: Summary of AMC methods.

FEATURE TYPE	CLASSIFIER			MOD.
	NN	SVM	DT	
ITD	[1][5] [20]	[14][8][5]	[29][14][32] [39],[24]	FSK
	[1][5] [20]	[9]	[29],[14], [32],[39][24]	ASK
	[1][5] [20]	[5][9]	[29],[14], [32],[39],[24]	PSK
	[1] [20][5] [43]	[9]	[29],[14], [32], [39],[24][24]	QAM
	[1][5][20]	[5]	[24]	AM,FM
			[39],[24][24]	MC
FT	[1]	[14]		ASK
	[1]		[9],[11]	PSK
	[1]		[9],[44]	FSK
	[1]		[9]	QAM
	[1]		[9]	AM/FM
				MC
WT	[27][16][17] [40]	[12][8] [13][15]	[29],[31],[39]	ASK
	[27][16][50] [47]	[8][13] [15]	[9][29][31] [23]	PSK
	[27][16][50] [47]	[12][13] [15]	[9][29][31] [23]	FSK
	[16][25][47]	[12][13]	[9][29][31] [23]	QAM
HOMs&Cs	[5][20][22] [30][17]	[19][29] [35][42]	[29][17]	ASK
	[33][5][5] [20][28][48] [47]	[19][8] [42]	[29][45][17] [23][39][7] [24][21]	PSK,
	[33][5] [22][48][47]	[42]	[29][17][23] [39][24]	FSK,
	[33][5] [22][48][47]	[19][8] [42]	[29][17][23] [39][7][24][21]	QAM
	[48]		[39],[24]	MC
CCs			[34]	ASK
			[18]	CPM
		[41]	[22],[34],[25], [36]	PSK,
			[22],[34],[25]	QAM
			[22],[34],[35],[46]	FSK
			[22],[35],[25]	AM
CS		[36]		QAM
ZC			[37],[38]	PSK, FSK
Entropy	[26][49]			

V. CONCLUSION

This paper has presented background martial which is essential for understanding the different techniques proposed for FB AMC methods along with review to relevant literature. A summary of these methods is presented in Table 2. Based on our findings, it is observed that SVMs attain higher classification rate than ANNs and that all PR techniques perform better than DT. However, DT is simple to design and implement as it can classify a wide range of modulation schemes by adding more decision points without the need to re-train the classifier as in PR techniques. It is also observed that much of published work has considered AWGN channel model and the results are mostly presented using computer simulations.

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