Accuracy Analysis of Feature-based Automatic Modulation Classification with Blind Modulation Detection

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***Abstract*— The process of automatic classification of a detected signal's employed modulation type has gained importance in recent years. The goal of such an approach is to maximize the achievable throughput for intelligent receiver designs in civilian applications as well as jamming malicious signals in military applications. Automatic Modulation Classification (AMC) increases in difficulty since there is no a-priori knowledge of transmitted signal properties, such as signal power, carrier frequency, or bandwidth, nor any associated link properties such as channel state information (CSI), noise characteristics, signal-to-noise ratio (SNR) or any offset in frequency and phase. The most complex, albeit also most realistic, scenarios for AMC are faced when considering Non-Gaussian noise with multipath fading in frequency selective and time-varying channels. Different methods have been proposed in the literature to estimate unknown signals and channel parameters for AMC. However, a key consideration in selecting among them is attaining low computational complexity in order for AMC to become a technique feasible for real-time applications. Predominantly, blind AMC and associated parameter estimation utilizes feature-based approaches, owing to their low-complexity calculations of statistical values. In this work, we have analyzed the accuracy of High-order Statistics-based (HoS) methods utilizing feature extraction approaches, Support Vector Machine classifiers, and estimation techniques to determine an optimized framework for different real-time applications.**

***Index Terms*— Automatic modulation classification, Blind modulation classification, Feature-based modulation classification, High-order Statistic-based (HoS) Features, Channel State Information (CSI).**

I. INTRODUCTION

The idea of Automatic Modulation Classification (AMC) originated from military applications. AMC is a challenging endeavor in the saturated electromagnetic spectrum of any battlefield scenario. In this application, friendly signals need to be securely transmitted and received, while unfriendly or malicious signals should be located and jammed. In this situation, an intelligent receiver is needed to operate in real-time, in order to intercept, detect, process and produce a final decision on whether a signal is classified as friend or foe. This is a highly complex task, yet requires real-time operation and thus needs to emphasize low-complexity computational approaches [1]. Beyond the military domain, AMC also has a host of civilian target applications. The rapid growth of wireless communication services in everyday use and the corresponding saturation of limited RF resources have increased the need for reusing frequency bands, as well as band sharing, and thus accelerated the demand for cognitive radios (CR) and intelligent receivers. Traditionally, in order for a correct process which a receiver can identify the transmitted signal modulation type and demodulation of the signal, the transmitter has to send supplementary information which includes the modulation type, either in-band or out-of-band. Automatic modulation classification can diminish this need and reduce associated overhead. This plays an important role in spectrum surveillance to efficiently reuse commercial spectrum and reduce the overhead at the receiver side. Cognitive Radios can change their transmitter parameters based on their operating environment, for example a change in spectrum utilization or the presence of a licensed operator in a shared band. Utilizing AMC in the cognitive radio, the receiver can detect the change in modulation type without the need for supplementary information transmission [2].
Generally, the objectives for a receiver equipped with AMC are: to achieve maximum probability of correct signal classification while minimizing the required observation interval, being capable of identifying many different modulations in diverse environments, being robust against model mismatches, achieve real-time functionality and low computational complexity.
Next we will discuss different methods for automatic modulation classification, all of which can be categorized into two principal categories.

- Likelihood-based (LB) approaches:
  Approaches in this category are composite hypothesis-testing problems and rely on the probability density function (PDF) of the observed waveform, conditioned on the embedded modulated signal, which contains all the information about the modulation type. This method is considered to be optimal in terms of its mathematical complexity, in a Bayesian sense. The decision is made by comparing a likelihood ratio against a threshold that is determined theoretically. There are two major flaws with this method; firstly, the computational complexity is high due to the need to compute multi-dimensional conditional PDFs of

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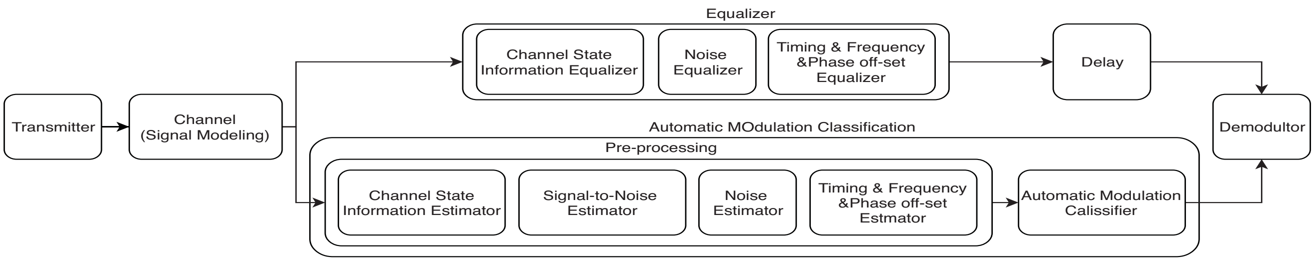

Fig. 1. Blind modulation classification system block diagram.

unknown parameters; secondly, perfect channel state information must be known or estimated, which causes LB-approaches to be computationally complex. In order to somewhat relax the computational complexity, three approximation techniques can be applied when computing the conditional PDFs of unknown parameters: – Average Likelihood Ratio Test (ALRT) – Generalized Likelihood Ratio Test (GLRT) – Hybrid Likelihood Ratio Test (HLRT). Unfortunately, because of the inner computational complexity of this approach, most research literature considers only Additive White Gaussian Noise (AWGN) in their signal model, which does not equate to a realistic scenario. What is needed is a technique that can significantly relax the computational complexity of this method resulting in a more accurate and applicable AMC approach [3], [4].

- Feature-based (FB) approaches:
  The design of a Feature-based modulation classifiers consists of two stages: 1) Pre-Processing 2) Classification. In the pre-processing stage, features of the inbound waveform is extracted and then a classifier is applied to the obtained results of the extracted features to determine employed modulation. Based on different environments and assumptions, various features can be selected. Generally employed features in literature are: – Signal Spectral-based Features – Wavelet Transform-based Features – High-order Statistics-based Features (including Cumulant-based and Moment-based features) – Cyclostationary Analysis-based Features – Graph-based Cyclic-Spectrum Analysis Features. The extracted features from instantaneous changes in the incoming signal includes instantaneous power, frequency, phase, etc. Because of the low-complexity calculations needed to extract these features, this approach is considered favorable for operation in real-time applications and is also more suitable for hardware implementations. Sometimes, two or three features are extracted in order to be able to obtain more accurate results in non-cooperative environments. Different modulations exhibit different feature traits for their detection. Hence, a single feature cannot be universally applied to detect all feasible modulation schemes with high reliability. Different classifiers have been proposed in the literature, such as maximum likelihood classifier, Distribution Test-based classifier and classifiers using machine learning methods. These classifiers also exhibit different computational complexity levels. The combination of different types of features with different classifiers provides for numerous possible automatic modulation classifiers. Unfortunately, employing the least computationally complex feature with the least computationally complex classifier will not provide acceptable results. As a consequence, at least one of the two stages has to be more computationally complex in order to achieve desirable results [5]–[7].

Estimation of unknown parameters usually is accomplished using a feature-based approach. These estimations usually take place during pre-processing, as shown in Fig. 1. Estimations made during the pre-processing stage can also be used as initial values for equalizers. A delay corresponding to the time required for AMC is applied. Furthermore, as shown in Fig. 1, some of the unknown parameters that are considered most impactful on the received signal quality should be estimated to prevent degradation of the results.

In this work, we introduce some of the most realistic channel state information (CSI) and phase offset estimators. These two factors have the most impact on the quality of the received signal. Moreover, we will discuss Signal-to-Noise (SNR) and noise information effects on the classification accuracy and computational complexity. Furthermore, classification accuracy of cumulant- and moment-based feature extraction combined with SVM classification is discussed in [8], [9].

The rest of the paper is organized as follows. In section II the channel state information (CSI) estimator, SNR discussion, noise information discussion and estimation of timing, frequency and phase offset are presented. In section III the classification analysis for cumulant-based approaches combined with SVM classification simulated in MATLAB is presented. In section IV, the analysis for moment-based approaches with SVM classification based on MATLAB simulation is discussed. Finally, in section V we present our conclusion on classification accuracy.

II. Estimation Techniques and Discussions

A. Channel State Information Estimation

The important unknown factor that can have significant influences on the received signal's quality is the Channel State Information. Most of the published literature assumes that channel state information is known at the receiver side, which makes these efforts less applicable to real-world applications [10]. Other employed techniques such as Least-Square Estimation, Zero Forcing (ZF) in the absence of noise, MMSE Estimation, Expectation-Maximization (EM) algorithm, Maximum-Likelihood (ML) Estimation, Gaussian ML Estimation and Training-based algorithms in order to estimate CSI at the receiver, many of which exhibit significant computational complexity and are thus not feasible for low-complexity real-time applications [11]–[17]. Consequently, research efforts focusing on solutions in the absence of a-priori information employing CSI estimators shifted towards using lower-complexity classification methods. This, however, results in a degradation of the accuracy of these types of classifiers. Some of these CSI estimators, such as Training-based algorithms, are not suitable for use in specific military application scenarios [18]–[21]. Below, we provide an analysis of a more realistic method [22]. Expectation-Maximization (EM) Estimator is known to be a realistic method for channel estimation because of its combination with Gaussian Mixture Model (GMM) noise. For the signal samples $r[1], r[2], ..., r[N]$ the likelihood of the n^{th} sampling belonging to the m^{th} component of the GMM model is calculated as shown below.

$$\chi(r[n], m) = \frac{1}{2\pi\sigma_m^2} \exp(\frac{-(r[n]-\mu_m)^2}{2\sigma_m^2}) \tag{1}$$

where σ_m is the variance and the corresponding soft membership, calculated by definition as:

$$z(n, m) = \frac{\chi(r[n], m)}{\sum_{m=1}^{M} \chi(r[n], m)} \tag{2}$$

For modulation classification, μ_m is the component mean, and its underlying structure can be expressed as a combination of channel gain and transmitted symbols: $\mu_m = h \cdot S_m$ where h is the channel coefficient and S_m is the m^{th} symbol in the modulation alphabet set. Furthermore, the noise variances of each Gaussian component are often considered identical as: $\sigma_m = \sigma$. The derivative with respect to channel coefficient and noise variance can be calculated, respectively, as:

$$\frac{\partial \log \chi(r, k)}{\partial h} = \sum_{m=1}^{M} \sum_{n=1}^{N} z(r[n], m)\gamma_m \frac{-2r[n] \cdot S_m + 2h \cdot S_m^2}{\sigma} \tag{3}$$

$$\frac{\partial \log \chi(r, k)}{\partial \sigma^2} = \sum_{m=1}^{M} \sum_{n=1}^{N} z(r[n], m)\gamma_m (-\frac{1}{\sigma^2} + \frac{(r[n] - h \cdot S_m)^2}{\sigma^4}) \tag{4}$$

where γ_m is the mixture proportion of the m^{th} component. By setting the above equations to zero the functions that update channel gain and variance are given, respectively, as:

$$h_{i+1} = \frac{\sum_{m=1}^{M} \sum_{n=1}^{N} z(r[n], m)\gamma_m r[n] S_m}{\sum_{m=1}^{M} \sum_{n=1}^{N} z(r[n], m)\gamma_m S_m^2} \tag{5}$$

$$\sigma_{i+1} = \frac{\sum_{m=1}^{M} \sum_{n=1}^{N} z(r[n], m)\gamma_m (r[n] - h_i \cdot S_m)}{\sum_{m=1}^{M} \sum_{n=1}^{N} z(r[n], m)\gamma_m} \tag{6}$$

where h_{i+1} and σ_{i+1} are the updated estimation of the parameters for iteration $i+1$. Equation (6) creates the update function of the expectation/condition maximization (ECM) algorithm using the channel coefficient estimated in the previous iteration [22]–[24].

B. Signal-to-Noise (SNR) Discussion

This property typically is unknown to the receiver. Therefore, all of the works in literature obtain their results based on different assumed SNRs ranging from -20 dB to 20 dB. Obviously, when SNR decreases, the probability of correct classification (P_{cc}) also decreases. Most of SNR estimation methods attempt to deploy a Newton-Raphson technique due to its simple calculations. This approach features a measure of control over the computational complexity through adjustments to the number of iterations or cycles required of the technique when performing that estimation. Fig. 2 illustrates that the estimator incurs a penalty when the SNR of the given channel decreases. Compared to a good channel, significantly more iterations are required to achieve results comparable to the outcome for a good high-SNR channel. This factor by which the number of required iterations increases can be seen as a low-SNR penalty, directly contributing to the overall computational complexity of the approach [8].

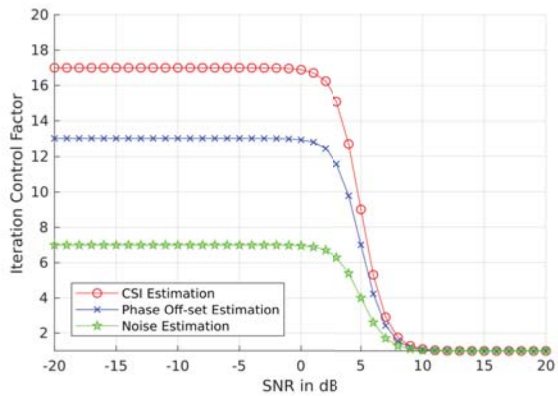

Fig. 2. Iteration Control Factor for the required number of iterations to achieve reliable estimation.

C. Noise Information

Virtually all research publications around AMC in the presence of noise assume that there is at least one known parameter: the noise variance. But in real-world scenarios we have no information about the noise. Hence, some equalizer is needed to compensate for the impact of the noise on the signal. By using equalizers, some pre-processing and computational complexity is added to the system, thus increasing processing time and implementation complexity.

D. Timing, Frequency and Phase Offset Estimation

This issue mostly relates to whether the application of automatic modulation classification is in the civilian or military domain. For civilian applications, most of the time transmitter and receiver are synchronized. Otherwise, like other unknown parameters, it is needed to use synchronization recovery methods to get receiver information about propagation delays. For military applications in which there is no information from the transmitter, synchronization methods have to be employed in order to achieve the best results. In feature-based classification, frequency and phase offset can cause progressive or constant constellation rotation, respectively, which can dramatically affect the performance of automatic modulation classification. Hence, these parameters should be estimated before classification. It is assumed that $arg(r(n))$ and $r^*(n)$ denote the argument and complex conjugate of $r(n)$, which is the received signal at the n^{th} time slot, respectively. The frequency offset ω_0 is estimated as:

$$\omega_0 = \frac{-2}{N_0 - 2} \sum_{n=1}^{N_0/2} arg(r(n) \cdot r^*(\frac{N_0}{2} + n - 1)) \tag{7}$$

with N_0 assumed to be an even number. Consequently, the phase offset estimator can be calculated as:

$$\theta_0 = arctan(\frac{\sum_{n=1}^{N_0/2} \Im[\hat{r}(n) \cdot \hat{r}^*(2n)]}{\sum_{n=1}^{N_0/2} \Re[\hat{r}(n) \cdot \hat{r}^*(2n)]}) \tag{8}$$

Where $\Im$ and $\Re$ denote the imaginary and real parts, respectively: $\hat{r}(n) = r(n) \cdot e^{-j\omega_0 n}$ [25].

III. Cumulant-based Classification Analysis

This classification approach has been widely utilized in literature for having suitable performance in low SNR compared to other features, and this feature usually is not significantly impacted by the presence of noise. Therefore, it reduces or eliminates the need to employ noise estimators and equalizers. This feature can also operate with short signal observation lengths, which makes it vastly more suitable for real-time low-latency applications. Cumulant-based classifiers can achieve good performance in the presence of carrier phase and frequency offset, which is discussed below. Cumulants of any order n can be calculated from the following recursive Moment-to-Cumulant formula:

$$C_m = M_n - \sum_{m=1}^{n-1} \frac{(n-1)!}{(m-1)!(n-m)!} C_m \cdot M_{n-m} \tag{9}$$

where the central moment of order n (about mean μ) is defined as:

$$M_n = \frac{1}{N} \sum_{k=1}^{N} (x - \mu)^n [k] \tag{10}$$

where N is the length of observation $x[k]$ of the received signal [5]. Extracting higher order cumulants leads to more accurate results. Next, we will evaluate the achievable accuracy of this method combined with SVM classifier while

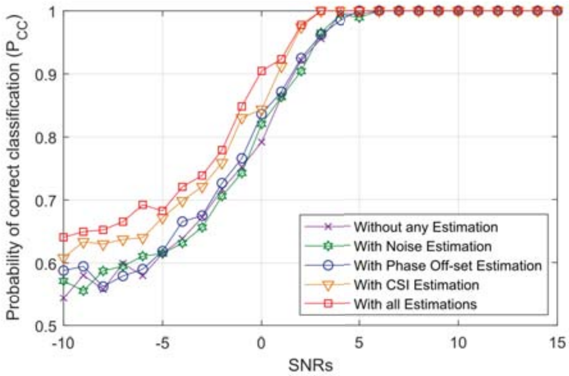

Fig. 3. P_{cc} with and without deploying CSI estimator in cumulant-based classifier.

blind modulation techniques are applied over relatively realistic signal model (multipath fading) [26]. Results are obtained by averaging over P_{CC} in different SNRs for different modulation types and shown in Fig. 3.

IV. Moment-based Classification Analysis

Unlike the cumulant-based approach discussed in the previous section, the moment-based classification approach is relatively sensitive to phase offset and noise. Therefore, in order to obtain the best possible results this approach requires the use of noise and phase offset estimators and equalizers. It is obvious that by incorporating estimators and equalizers the computational complexity will increase, which was shown above in Fig. 2. However, this design change also yields higher overall results. In Fig. 4, the accuracy of a moment-based method combined with SVM classifier is analyzed while utilizing channel state information, phase offset or noise estimation individually or in combination. Results are obtained by averaging over P_{CC} at different SNRs for different modulation types [9], [27].

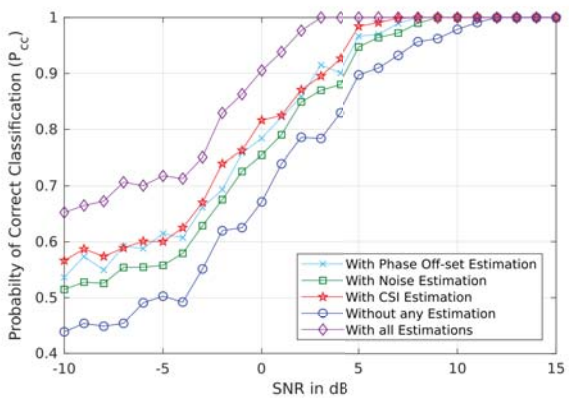

Fig. 4. P_{cc} with and without deploying CSI, phase offset and noise estimation in moment-based classifier.

V. Conclusions

In this paper, we presented our insights and results from analyzing Feature-based pre-processing coupled with Support Vector Machine classification employed for AMC. We presented the achievable system performance both with and without utilizing estimations in blind modulation classification. Although we could achieve higher results by deploying higher performance estimators which produce much higher computational complexity, the drastic increase in computational complexity associated with the use of these estimators significantly impacts the feasibility of utilizing such a strategy in real-time AMC systems. Cumulant-based feature extraction achieves higher performance without deploying any estimation for blind modulation classification. More importantly, owing to the comparative simple calculations needed to extract these features the resulting low computational complexity makes these far higher suited for implementations in real-world applications that demand low-latency real-time processing.

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