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Research Paper

Low-complexity Automatic Modulation Classification of Higher-order QAM Based on Square Modulus Extraction

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A B S T R A C T

Modulation classification is a core function of cognitive radio, essential for signal identification, menace assessment, and dynamic spectrum management. Quadrature Amplitude Modulation (QAM) has become an important modulation scheme used in most civilian and military applications. However, algorithms developed so far for these purposes have been limited in classifying higher-order QAM and are also extremely complex. Applications which need to take real-time critical decision based upon modulation types information require that an automatic modulation classification (AMC) algorithm is necessarily simple both in cost and in implementation. This paper, therefore, proposes a novel low-complexity feature-based (FB) method based on evaluating the square modulus of the baseband demodulated received signal, as the only discriminating feature, to classify QAM of any modulation order. Results show, in the presence of combined effects of the carrier phase deviations, timing offset, multipath interference and AWGN, that all QAM modulation types up to 2048-QAM achieve 100% classification accuracy at lower than 10 dB of SNR. The classification algorithm is thus robust in accurately classifying any QAM modulation type even in the presence of combined effects of the common distortions on the received modulated signal.

INTRODUCTION

Modulation classification plays a key role in decoding cognitive radio, signal identification, menace assessment, spectrum senses, and management, efficient use of available spectrum and increase in the speed of data transfer. Modulation classifier estimates characteristics of a radio signal and determines the modulation type based on these characteristics. These signal characteristics include the carrier phase deviations, amplitude imbalance, and internal receiver noise, additive white Gaussian noise, fading and multipath. The modulation type represents the substantial feature in modern radio systems to give knowledge on modulation signals and can be used in decoding both civilian and military applications such as cognitive radio, signal identification, menace assessment, spectrum senses, and management, efficient use of available spectrum and increase in the speed of data transfer [1].

A modulation classifier can be described as a system comprising of pre-processing, feature processing and classification [2]. Classification algorithms can be divided into two categories: pattern recognition method, or feature-based (FB) technique, which relies upon the feature extraction ideas, [3] and decision theory method, or likelihood-based (LB) technique, which is based on maximum likelihood [4]. The LB, which is based on Bayesian theory, computes the probability functions of all possible modulation schemes for the received signal and selects the one with the best likelihood. In theory, LB algorithms based on ML criterion are computationally expensive and have narrow applicability, even though it is adjudged the best. Besides, they often require extensive knowledge all signal parameters which may be impossible to estimate at the receiver. On the other hand, the FB which simply finds features that can distinguish different modulated signals, such as wavelet domain features [5], cyclic spectrum [6], and high-order statistics [7-8], has a reduced complexity, which makes it recognized as a viable alternative to LB techniques [9]. The quality of these features is what significantly influences the performance of the FB classifier.

The FB are more straightforward, and often require reasonable SNR to distinguish signal points especially when the number of signal point increases. Machine learning approach has also been explored as an FB scheme in which support vector machines (SVM) [10-11], decision trees [12-13] and neural networks [14-15] are commonly used to extract features of the signals automatically for modulation classification. However, high computational complexity, high recognition times, and extensive training data may limit real-time application, especially in noisy channels.

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Deep learning algorithms have recently been developed [16-17], and are found to outperform traditional machine learning algorithms in high noise environments. In [18], cascaded feature fusion in which multiple classifiers such as the high-order cumulant, decision fusion of decision tree, convolutional neural network, and support vector machine are all combined in cascade is used to classify AM, FM, 2 ASK, 2 FSK, 4 FSK, BPSK, QPSK, 8-PSK, 16-PSK, 8-QAM, 16-QAM, 32-QAM and 64-QAM, achieving only about 93.25% recognition rate for MQAM at 10dB. However, cascading multiple classifiers in cascade in order to achieve such a performance is prohibiting in real-time applications. The authors in [19] have used machine learning algorithms based on the K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN) to classify analog and digital modulations with recognition rates not exceeding 74.7% and 90.5%, respectively; and the recognition for 4-QAM at these rates were obtained only after SNR of 10dB. The works in [20] developed an automatic modulation classification based on artificial neural network (ANN) to classify four types of digital modulation: BPSK, QPSK, 16-QAM and 64-QAM, in which their algorithm was claimed to have achieved a recognition probability of approximately 97-99% in the signal-to-noise ratio (SNR) range of 7-30 dB for each phase offset value. However, the time it takes to train the network, as with other machine learning algorithms, is still a challenge especially at low SNR values. Applications which need to take real-time critical decision based upon modulation types information requires that an AMC algorithm is necessarily simple both in cost and implementation. Besides, most of the machine learning approaches have not been able to classify QAM signals beyond 64-QAM. Because with QAM, the computational complexity increases with increasing modulation order and will make implementation prohibitive.

Therefore, a novel low-complexity FB method based on evaluating the square envelope or the square modulus of the baseband demodulated received signal is proposed, as the only discriminating feature, to classify QAM of any modulation order. The method, unlike the LB classifiers; requires no knowledge of transmitted signal parameters. Unlike pattern-based or machine learning classifiers, this method requires no constellation analysis, higher-order statistics, or extensive data training. The proposed algorithm assumes that the receiver does not have a priori knowledge of any signal parameter, except that a square-root-raised cosine (SRRC) filter, as usual with QAM transceivers, must have been used to pulse shape the message at the transmitter. The received signal will, first of all, be demodulated with orthogonal carrier signals and then be simultaneously low-pass filtered and un-pulse shaped with a matched SRRC filter. However, the span of and the roll-off factor of the SRRC pulse shape at the receiver need not exactly match that at the transmitter. The signal parameter for classification is then extracted in the presence of signal distortion such as symbol timing offset, carrier phase offsets, AWGN and multipath interference. Finally, to confirm the robustness of the proposed classifier, percentage of classification accuracy is obtained for different signal distortion over a certain range of SNR values.

METHOD

Signal and Channel Model

Let the transmitted designated as $x(t)$. This signal during propagation is distorted by phase deviation $\emptyset_0$, timing offset τ, multipath impulse response h, and AWGN, and so the received is a distorted version of $x(t)$ and it will be designated as $v(t)$. At the receiver, $v(t)$ is first sampled at $t = kT_s$, where $T_s = T/S$, T is the symbol time and S is the oversampling factor. The sampled signal $v(kT_s)$ is then demodulated with orthogonal digital carrier wave $e^{-j(2\pi f_c kT_s)}$ as:

$$\begin{aligned} z(kT_s) &= v(kT_s)e^{-j(2\pi f_c kT_s)} \\ &= \{h(kT_s)x(kT_s-\tau)e^{j\{\emptyset_0(kT_s)\}} + \\ &\qquad w(kT_s)\}\, e^{-j(2\pi f_c kT_s)} \end{aligned} \tag{1}$$

$z(kT_s)$ is low-pass filtered and un-pulse shaped by a matched SRRC, and then appropriately downsampled to baseband signal $z[kT]$ at symbol time $T = 1$ second. If $x[kT]$ are QAM samples, the demodulated based samples can be expressed as

$$\begin{aligned} z[k] &= h[k]s_1[k-\tau]cos(\emptyset_0[k]) - h[k]s_2[k- \\ &\quad \tau]sin(\emptyset_0[k]) + 2w[k]cos(2\pi f_c k) \\ &\quad +j\{s_1[k-\tau]h[k]sin(\emptyset_0[k]) + [s_2[k- \\ &\quad \tau]h[k]cos(\emptyset_0[k]) - 2w[k]sin(2\pi f_c k)\} \end{aligned} \tag{2}$$

Feature Extraction and Proposed Classifier

The extracted signal parameter from the received signal $z[kT]$ in Eq. 1 is the instantaneous square modulus (square envelope) expressed as:

$$\begin{aligned} |\psi[k]|^2 &= h[k]^2(s_1[k-\tau]^2 + s_2[k-\tau]^2) + 4w[k]^2 \\ &\quad + 4w[k]h[k]\{s_1[k-\tau]cos(\emptyset_0[k]) - \\ &\quad s_2[k-\tau]sin(\emptyset_0[k])\} \end{aligned} \tag{3}$$

When $h = 1$ (unity multipath channel), $w = 0$ (zero gain AWGN channel) and $\tau = 0$ (no timing offset), the square modulus reduces to

$$|\psi[k]|^2 = {s_1}^2[k] + {s_2}^2[k] \tag{4}$$

The best approximation to the largest constellation value is expressed as

$$\widehat{M} = ceil\left(\sqrt{max(|\psi[k]|^2)/2}\right)^2 \tag{5}$$

Where the maximum of the square modulus is first halved and the square root of it is rounded up towards plus infinity before the resulting quantity is eventually squared. $\widehat{M}$ is an approximation that corresponds with the largest constellation value of the received QAM symbols. This approximation is obtained in the presence of phase deviations, timing offset, AWGN, flat fading and multipath interference on the transmitted channel. The actual modulation order M can then be obtained as

$$M = 2^{\{round(log_2 \widehat{M})\}} \tag{6}$$

M, therefore, represents the actual modulation order of a square QAM such as 4-ary, 16-ary, 64-ary, 256-ary and 1024-ary QAM, or non-square QAM such as 8-ary, 32-ary, 128-ary, 512-ary and 2048-ary QAM.

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RESULTS AND DISCUSSION

The number of symbols generated is N=1000, the period for each symbol is $T = 1s$ and the oversampling factor is $S = 4$ so that the $T-$ spaced message signals are oversampled with S in order to satisfy the Nyquist criterion. Similarly, the carrier frequency, $f_c = 10^9\ Hz$ is oversampled with S so that the received modulated passband signal is sampled at sampling rate, $f_s = 4 * 10^9\ samples/sec$. The SRRC pulse-shaping filter with energy of 1 Joule, symbol span L ($L = 8$), roll-off factor of $\alpha = 0.5$ (corresponding to $1/2$ of the sampling rate) is used at the transmitter. The received modulated signal is simulated through an AWGN channel using Matlab built-in function *awgn* with varying SNR= $\{0, 2, \ldots, 30\}$ dB, is demodulated with orthogonal carrier waves, and then simultaneously low-pass filtered and un-pulse shaped using a SRRC with symbol span L ($L = 2 * S$), roll-off factor of $\alpha = 1$ (corresponding to pure raised cosine) at the receiver. We analyze the performance of the classifier with respect to distortions such as phase deviation (frequency offset, initial phase offset and phase noise), timing offset, multipath interference and AWGN at various SNR values. For classification of modulation with different SNR values, we obtain accuracy percentages by executing algorithm 100 times and calculating the ratio between correct classification and total number of executions. When classification is performed in the presence of AWGN alone (no other distortion), the top plot of Figure 1, for square QAM, shows that only 256-QAM achieves 100% classification accuracy at all SNR values under consideration while 1024-, 64-, 4-, and 16-QAM achieves the 100% classification accuracy only at 2 dB, 4 dB, 6 dB, and 8 dB, respectively. However, in the lower plot of figure 1, for the non-square QAM, it is shown that 100% classification accuracy is achieved by only 2048-QAM at all SNR values while 128-, 512-, 32-, and 8-QAM achieves the 100% classification accuracy only at 2 dB, 4 dB, 4 dB, and 10 dB, respectively. Therefore, under the effect of awgn only 256-QAM and 2048-QAM prove to be the most robust modulations in terms of ease of identification. Although, both the 32-QAM and 512-QAM are distinguishable, they offer same ease of identification.

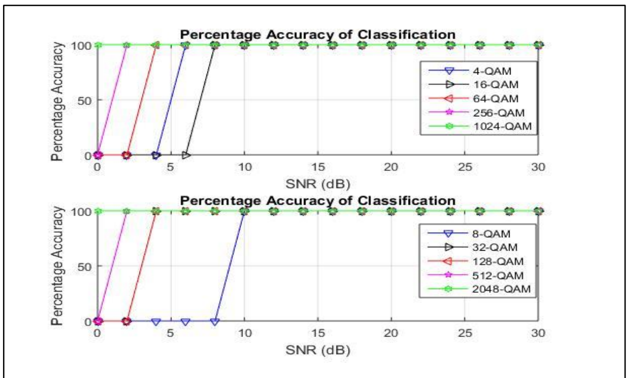

Figure 1. Accuracy Percentage of classification over AWGN channel only

When phase deviation comprising of phase offset $\theta_0 = 1.2$, frequency offset $f_0 = 40{,}000\ Hz$ at a carrier frequency of $f_c = 10^9\ Hz$ and phase noise distribution $\varphi_o(t)$ are jointly applied to corrupt the transmitted signal over the AWGN channel, the top plot of figure 2, for square QAM, shows that only 1024-QAM achieves 100% classification accuracy at all SNR values, while 256-, 64-, 4-, and 16-QAM achieves the 100% classification accuracy only at 2 dB, 4 dB, 6 dB, and 8 dB, respectively. However, in the lower plot of figure 2, for the non-square QAM, it is shown that 100% classification accuracy is achieved by only 2048-QAM at all SNR values while 512-,128-, 32-, and 8-QAM achieves the 100% classification accuracy only at 2 dB, 4 dB, 4 dB, and 10 dB, respectively. Therefore, under the combined effects of phase deviations and awgn, higher-order QAM such as 1024-QAM, and 2048-QAM are found to be the most robust modulations in terms of ease of identification. However, both 128-QAM and 32-QAM offer similar ease of identification.

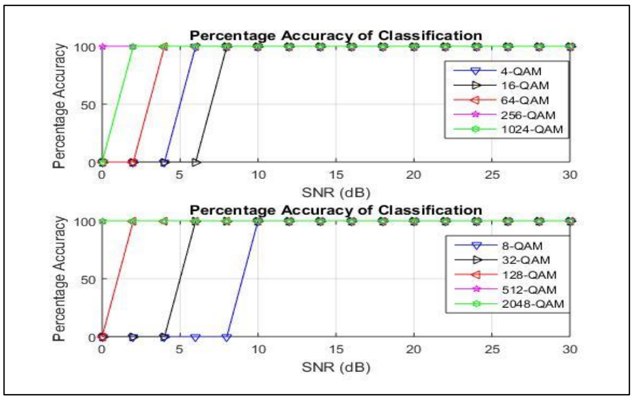

Figure 2. Accuracy Percentage of classification with phase deviation over AWGN channel

The phase deviation comprising of phase offset $\theta_0 = 1.2$, frequency offset $f_0 = 40{,}000\ Hz$ ($40\ ppm -$ parts per million) at a carrier frequency of $f_c = 10^9\ Hz$, phase noise distribution $\varphi_o(t)$ and timing offset $\tau = 0.5$ are jointly applied to corrupt the transmitted signal over the AWGN channel. The top plot of figure 3, for square QAM, shows that only 256-QAM achieves 100% classification accuracy at all SNR, while 1024-, 64-, 4-, and 16-QAM achieves the 100% classification accuracy only at 2 dB, 4 dB, 6 dB, and 10 dB, respectively. The effect of timing offset only penalizes the 16-QAM to require additional SNR of 2 dB in order to achieve the 100% compared to what were obtained in Figure 2. However, in the lower plot of figure 3, for the non-square QAM, it is shown that 100% classification accuracy is achieved by only 2048-QAM at all SNR values while 512-,128-, 32-, and 8-QAM achieves the 100% classification accuracy only at 2 dB, 4 dB, 4 dB, and 10 dB, respectively. Therefore, under the combined effects of phase deviations, multipath and awgn only higher-order QAM such as 256-QAM and 2048-QAM are the most robust modulations in terms of ease of identification. However, both 128-QAM and 32-QAM offer similar ease of identification.

Figure 4 depicts classification accuracy of QAM signal received with phase deviation comprising phase offset $\theta_0 = 1.2$, frequency offset $f_0 = 40{,}000\ Hz\ (40\ ppm)$ at a carrier frequency of $f_c = 10^9\ Hz$, phase noise φ_o and timing offset $\tau = 0.5$ in the presence of mild multipath interference and AWGN at different SNR, the top plot of figure 4, for square QAM, shows that 1024-, 256-, 64-, 4-, and 16-QAM achieve the 100% classification accuracy only at 2 dB , 6 dB, 6 dB, 6 dB, and 16 dB, respectively, requiring additional SNR of 2 dB each for 64-

QAM and 4-QAM, and 6 dB for 16-QAM to achieve 100% accuracy of classification.

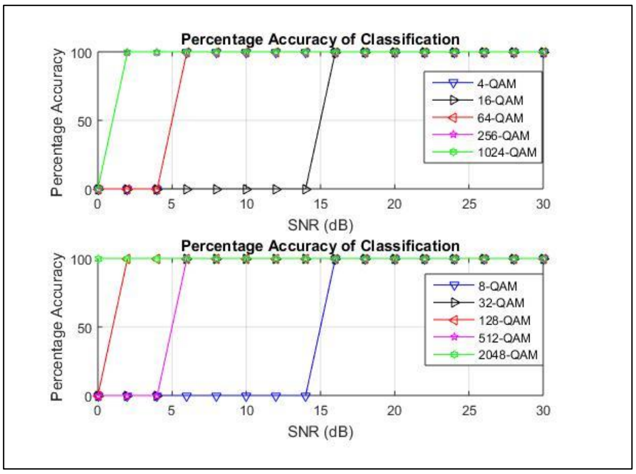

Figure 3. Accuracy Percentage of classification with phase deviation, and timing offset over AWGN channel

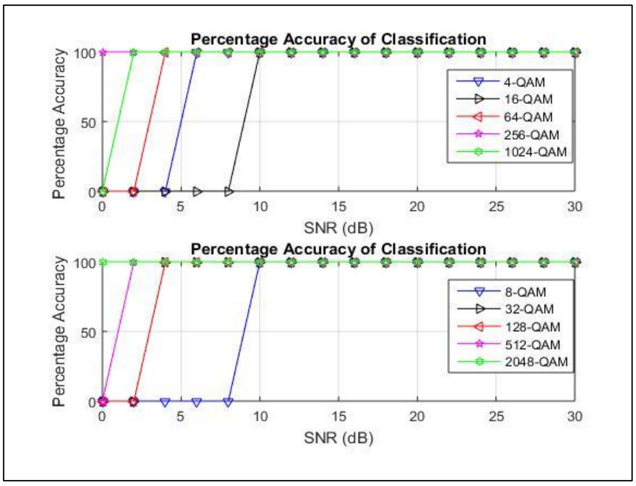

Figure 4. Accuracy Percentage of classification with phase deviation, timing offset and multipath interference over AWGN channel

However, in the lower plot of figure 4, for the non-square QAM, it is shown that 100% classification accuracy is achieved by only 2048-QAM at all SNR values while 512-, 128-, 32-, and 8-QAM achieves the 100% classification accuracy only at 2 dB, 6 dB, 6 dB, and 16 dB, respectively, requiring additional SNR of 2 dB each for 128-QAM and 32-QAM, and 6 dB for 8-QAM to achieve 100% accuracy of classification. Therefore, under the combined effect of phase deviations, timing offset, multipath and awgn only 2048- QAM appears to be the most robust modulations in terms of ease of identification while penalizing 4-QAM, 32-QAM, 64-QAM and 128-QAM with additional SNR requirement of 2 dB, and 8-QAM and 16-QAM with additional SNR requirement of 6 dB.

CONCLUSIONS

In this paper, the square modulus of demodulated received signal, as the only discriminating feature, in the presence of distortions such as carrier phase offset, timing offset, multipath interference and AWGN is extracted as the signal parameter. This parameter is then used as the feature for discriminating and classifying the QAM modulation type. The classifier requires no prior knowledge of the transmitted signal parameter, except that a SRRC filter, as usual with QAM signal, must have been used to pulse shape the message at the transmitter. Therefore, a SRRC length of twice the length of the oversampling factor is used with a roll-off of 1 (corresponding to pure raised cosine) at the receiver. This makes a perfect SRRC match unnecessary.

The square modulus is then used to compute the classifier, which provides a very low complexity in terms of both computation and time. Results show that when Additive White Gaussian Noise (AWGN) is the only distortion in the received signal, 256- and 2048-QAM achieve 100% classification accuracy while others achieve the 100% at different SNRs but less than 10 dB. When phase deviations are added to AWGN to corrupt the transmitted signal, only 1024-QAM, and 2048-QAM can achieve 100% classification accuracy while others achieve the 100% at different SNRs but still less than 10 dB. When timing offset is added, only 256-QAM and 2048-QAM achieve 100% classification accuracy while only 16-QAM is penalized with additional SNR requirement of 2 dB in order to achieve 100% classification accuracy. Under multipath conditions, only 2048-QAM maintains 100% classification accuracy. All other schemes require an additional 2 dB (4, 32, 64, 128-QAM) or 6 dB (8, 16-QAM) of SNR to achieve perfect accuracy.

Generally, the results show that even in the presence of all the distortions, 100% classification accuracy is achieved for all QAM modulation types below 10 dB of SNR. Therefore, the classification algorithm is not only of low complexity, it is robust in accurately classifying any QAM modulation even in the presence of combined effects of the carrier phase deviations, timing offset, multipath interference and AWGN on the received modulated signal.

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