Artificial Bias Induction in Fourth-Order Cumulants Based Automatic Modulation Classification Algorithm in AWGN and Multipath Propagation Channel

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Abstract. *Automatic modulation classification (AMC) represents a wide used technique for modulation format recognition of signals considered to be a priori unknown. Due to the low algorithm and hardware complexity, AMC algorithms based on fourth-order cumulants are still very popular. Presence of bias in standard cumulants estimated values of real signals constellations has positive impact on classification score for distinguishing real from complex signals. Therefore, one new approach in AMC is proposed in this paper, with focus on manipulation with theoretical expected cumulant values of real signals constellations, assuming artificially introduced bias will improve AMC performance. Artificial bias induction is done through modifications of standard cumulants mathematical formula. Performance of modified and standard fourth-order cumulants based AMC algorithms were explored in context of real and complex signals constellations. This was done through Monte Carlo simulations in propagation conditions which included Additive White Gaussian Noise (AWGN) and multipath propagation channel with known and unknown impulse response. Evaluation was done through the probability of correct classifications. Presented numerical results confirmed superiority of algorithm based on artificial bias induction in classification of real and complex signals, in each considered propagation scenarios, especially in a radio environment with lower signal-to-noise ratio (SNR) values. The remarkable AMC performance enhancements are up to 25%.*

Keywords

AMC, AWGN, bias, Binary Phase Shift Keying (BPSK), channel impulse response, cumulants, multipath, Quadrature Amplitude Modulation (QAM)

1. Introduction

Automatic modulation classification (AMC) represents an important system's process for performance improvement of different modern wireless systems and applications. It stands for technique of modulation recognition process of the received signal, without a priori knowledge about its parameters. Information obtained by AMC is then used for further demodulation of that signals. AMC found a significant importance in both military and civilian commercial systems and applications, such as cognitive radio, spectrum management, surveillance, software-defined radio (SDR), Internet-of-Things (IoT), smart reconfigurable transceivers, etc. [1–5].

After decades of development, AMC algorithms have diverged into two main categories: traditional recognition methods and Deep-Learning (DL)-based recognition methods [6]. The traditional AMC approaches can be also broadly divided into two types: likelihood-based (LB) hypothesis testing [7] and feature-based (FB) [8], [9]. LB is rooted in Bayesian theory and aims to achieve the optimal estimation of modulation schemes by minimizing the probability of misclassification. Although these methods are theoretically optimal, their excellent performance comes at the price of significant complexity what limit their practical application. From the other side, FB algorithms are based on pattern recognition approach, its determination, extraction of variable features of interest and their further processing for classification purposes. The common features include constellation features [10], statistical parameter features [11], wavelet transform features [12] etc. With the increasing complexity of communication systems and the demand for rapid response DL-based AMC technology has emerged.

To meet current AMC application requirements, for extended performance, complex classifiers are used for additional support of cumulant features, such as deep neural networks for fading channels [13], or DL methods [14], considered for various sets of digital signals' constellations. Many modern algorithms perform extraction of several different features simultaneously and combine their classification properties to improve performance. Higher order cumulants (HOCs) have good performance under the additive white Gaussian noise (AWGN) channel, but their performance degrades under fading channel. To overcome degradation under multipath propagation channels algorithm based on mathematical manipulation and new forms of fea-

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tures generation of HOCs is proposed in [15]. Cyclostationarity-based modulation classification of linear digital modulations in flat fading channels was explored in [16]. Also, the state of the art (SOTA) works reported high performance of algorithms for modulation recognition based on emerging DL technologies. In [17] composite deep convolutional neural network (CNN) architecture known as the composite dense-residual neural network (CDRNN) is used with focuses on enhancing the feature extraction and identification, aiming to achieve accurate recognition of modulation types with fading channels. The focus on high recognition accuracy is leading to large model size and high computational complexity, as well as issue of training and test time [18], which is improved by using of CNN [19]. From the other side, FB algorithms, even they were developed on the very beginning of the AMC research process, are still in researchers' focus resulting with additional performance enhancements. The most popular feature of interest in FB AMC is higher order statistics (HOS) – moments and cumulants, whereas cumulants have some advantages what make them especially interesting. AMC algorithms based on HOCs, i.e. fourth-order can still be treated as SOTA in AMC [20]. AMC based on fourth-order cumulants (construction of feature vector, then using mean and covariance matrix of that vector) is proposed in [12]. All these additional improvements still ensure their superiority in terms of hardware requirements, real-time applicability, low algorithm complexity and other relevant aspects for implementation, in comparison with other modern methods based on artificial intelligence, neural networks, machine learning etc. [21], [22]. They also show to be superior in low computational complexity, memory requirements, and inference time when compared with other up-to-date AMC algorithms, like neural networks (with difference measured in several orders of magnitude) – but requiring additional performance improvements to remain competitive with those algorithms [23].

An insight into published research of these algorithms and their performance, shows that most frequently complex signals constellations (commonly M-array Quadrature Amplitude Modulation (MQAM)) were considered in propagation conditions with AWGN as a main source of signal degradations. M-array Phase Shift Keying (MPSK) and MQAM classification in flat fading channel, and some advanced features generation algorithm were reported in [16]. Modulation classification of among the others and different MPSK and MQAM signals in AWGN and multipath channels were subject of research in [24]. Binary Phase Shifting Key (BPSK) modulation signals were considered in [25] under LB classifier and under CNN in [26]. In addition, other Pulse Amplitude Modulation (PAM) signals (PAM-4 to PAM-64) have also been subject of research in [1], under AWGN.

Due to realistic working conditions (which include at least channel with AWGN) and degradation of signals some dispersion of normalized cumulants' estimates around theoretical values is always present. This distribution phenomenon was explored and explained for sixth-order estimated cumulants originally in [27]. An interesting effect is the presence of the bias in distribution of estimated cumulants values of real signals' constellations due to cumulants' formula structure. It was shown that lower Signal-to-Noise (SNR) values generate strong bias for real signals' estimates. From the other side, it was reported that cumulants estimates of complex constellations are unbiased. Also, if unbiased variant of cumulants' mathematical formula is used, theoretically expected values for complex signal constellations remain the same [21]. These effects have direct impact on improved performance of cumulants based algorithms in distinguishing real signal constellations from complex signal constellations [1].

Therefore, one new approach is proposed in this paper. It is based on modification in terms of mathematical manipulation over standard fourth-order cumulants formula used in [3]. That is done with purpose to artificially induce bias and consequently to decrease theoretically expected cumulants' values of real signals, which will make distance between expected theoretical values of cumulants of adjacent real and complex signals getting larger. In this way, hypothesis made in this paper is that artificial bias induction of estimated cumulants of real signals can improve classification of various real from complex signals constellations. It will lead to better decision process and additional improvement of AMC performance in total in comparison with standard fourth-order based algorithm.

The performance of a novelly proposed algorithm based on artificial bias induction is evaluated through the value of introduced parameter, probability of correct classification, P_{cc}. A comparative analysis is conducted with standard fourth-order cumulants based algorithm for signals that have been modulated as real or complex signals. Tested scenario in this paper included real (BPSK) and complex (QPSK, 16-QAM, 64-QAM) signal constellations. Besides channel with AWGN only, performance of the tested algorithms was analyzed under multipath channel conditions as well. In this context, channel with known and unknown impulse response was used during simulations conducted for performance evaluation.

Considering this, focus in this paper was on the design of low complexity AMC algorithm for high-demanding real-world propagations scenarios, while maintaining simplicity and improving high accuracy. The main contributions are summarized as follows:

- An efficient model that can enhance AMC performance over standard fourth-order cumulants based AMC up to 25%, keeping the low complexity. Low computational complexity benefits real-time applications (i.e. intelligent communication receivers, cognitive radio, spectrum sensing, IoT).
- Improved classification accuracy even in high-demanding radio environment including multipath channel with unknown impulse response whose coefficients need to be estimated. The proposed algorithm can be further improved in the field of channel coefficient estimation by using an advanced SOTA algorithms.
- Classification accuracy with low computational com-

plexity in level of SOTA algorithms based on traditional cumulants and DL-based.

The paper is organized as follows: considered standard and novelly proposed artificial bias induction fourth-order cumulant based AMC algorithms are described in Sec. 2. and Sec. 3, respectively. Estimation of cumulants values in multipath propagation conditions is shown in Sec. 4. Simulation results and discussion are presented in Sec. 5, while conclusion is given in Sec. 6.

2. AMC Algorithms Based on Standard Fourth-order Cumulants

The received signal sequence, corrupted by AWGN, is commonly expressed as:

$$y(n) = x(n) + g(n) \tag{1}$$

with $x(n)$ being transmitted symbols whose modulation format being a priori unknown, while $g(n)$ stands for samples of zero mean AWGN having variance of σ_g^2. If zero-mean random variable x is associated with transmitted sequence $x(n)$, its second-order cumulant in structure of cum(x,x^*), where x^* denotes conjugate value of x, is defined as:

$$C_{21,\mathrm{x}} = E\left(|x|^2\right) \tag{2}$$

where $E(\,)$ represents mathematical expectation, which is realized as an average value over observed signal samples.

According to joint cumulant generating formula [28] the standard fourth-order cumulant of random variable x in structure cum(x, x, x^*, x^*) is defined as:

$$C_{42,\mathrm{x}} = E\left(\left|x^4\right|\right) - \left|E\left(x^2\right)\right|^2 - 2E^2\left(\left|x^2\right|\right). \tag{3}$$

The normalized fourth-order cumulants, $\hat{C}_{42,\mathrm{x}}$ is defined as:

$$\hat{C}_{42,\mathrm{x}} = \frac{C_{42,x}}{(\mathrm{C}_{21,\mathrm{x}})^2}. \tag{4}$$

Normalized values are necessary as the signal power at the receiving side is not a priori known, and thus to avoid potential problems with different signal power levels for the same modulation type signals, as well as for the different modulation types.

For AWGN, only the first and second order cumulants exist (for orders larger than two cumulant value is zero). Due to this characteristic of normal distributed random variables and the additivity feature of cumulants, it is possible based on estimated fourth-order cumulants of the received signal $y(n)$ to estimate fourth-order cumulants of the random variable $x(n)$ respectively [29].

In analogy, for random variable y, associated with the sequence $y(n)$ from (1), for propagation conditions in form of channel with AWGN only, corresponding cumulants of the received signal is related to cumulants value of the transmitted signal as:

$$C_{42,\mathrm{y}} = C_{42,\mathrm{x}}, \tag{5}$$

$$C_{21,\mathrm{y}} = C_{21,\mathrm{x}} + \sigma_{\mathrm{g}}^2. \tag{6}$$

Finally, if cumulants of transmitted signals are expressed over cumulants of received signal by combining (5) and (6), and by inserting it in (4), the following relations between cumulant values of signals x and y stand as:

$$\hat{C}_{42,\mathrm{x}} = \frac{C_{42,\mathrm{y}}}{(\mathrm{C}_{21,\mathrm{y}} - \sigma_{\mathrm{g}}^2)^2}. \tag{7}$$

The detailed derivation of the formulas is shown in [30]. The numerical value of the fourth-order normalized cumulants can be used for modulations classification needs, since this value is different for all considered modulations techniques. The modulation classification is executed via comparison of calculated values of normalized cumulants' estimates with predefined threshold values. Optimal thresholds are positioned at the middle of successive intervals corresponding with theoretical values for every particular modulation format under observation.

3. AMC Algorithm Based on Artificial Bias Induction in Standard Fourth-order Cumulants

A novel proposed algorithm is based on exploitation of standard fourth-order cumulant mathematical formula structure. By adequate manipulation over mathematical form in (3) artificial bias is inducted, and theoretically expected value of cumulants of real signal constellations is changed in that manner it is decreased (shifted left on a horizontal axis). In this way, thanks to existing bias phenomenon and its additional artificial induction, cumulants' estimates of real signals are additionally moved to the left from the original theoretical value generated based on (3). That means estimated cumulants' values of real signals are distributed around a new theoretical value, which is now on a longer distance from theoretical cumulants' values of the adjacent complex signal. It is assumed it will create preconditions for more accurate results in terms of modulation classification between real and complex signal constellations, and consequently on a total score of modulation recognition process.

The subject of modification is the second member in (3), because theoretical values of real signals cumulants are directly related to that. By multiplying the second member in (3) with introduced bias coefficient K, which is chosen as some positive number from a set of integers, the proposed modified formula for the fourth-order cumulant, labelled as $C_{42,\mathrm{xm}}$ is obtained as:

$$C_{42,\mathrm{xm}} = E\left(\left|x^4\right|\right) - K\left|E(x^2)\right|^2 - 2E^2\left(\left|x^2\right|\right). \tag{8}$$

In that manner, artifical bias is inducted and the modified theoretical value of fourth-order cumulant of BPSK signal constellation is decreased for bias coefficient K and it is calculated as:

$$C_{42,\mathrm{xm}}(\mathrm{BPSK}) = -1 - K\ . \tag{9}$$

It should be noted that case $K = 1$ corresponds to standard formula (3) [28], and the other chosen values (higher than 1) for bias coefficient K correspond to the proposed modified AMC algorithm. Theoretical values of normalized fourth-order cumulants, for considered BPSK, QPSK, 16-QAM and 64-QAM constellations, for cases $K = 1$, $K = 2$ and $K = 10$ are given in Tab. 1. This was verified by numerical analysis using MATLAB software tool, by calculating the estimates of normalized fourth-order cumulants $\hat{C}_{42,\mathrm{x}}$ for each of the modulation formats from the observing set {BPSK, QPSK, 16-QAM, 64-QAM}, where the mathematical expectations in (2) and (3) were calculated in the form of mean values over the ensemble of corresponding symbols for each modulation technique of interest.

Modification of bias coefficient K does not affect theoretical values of cumulants of complex signal constellations. Due to artificial bias induction (for $K > 1$) and produced artificial changes in theoretical values for BPSK accordingly, additional analysis in this paper included a scenario with threshold adjustment. An assumption is that it will additionally improve results for differentiation between BPSK and QPSK signal constellations, and consequently total results of modification recognition process. For example, by using standard cumulant formula (3) the theoretically expected value of cumulant for BPSK signal is –2 (for $K = 1$) and accordingly the threshold value for differentiation between BPSK and the nearest complex constellation, QPSK, is set to the value of –1.5. The threshold is obtained as the value in the middle of successive intervals corresponding with theoretical values for BPSK and QPSK. For $K = 2$, the theoretically expected value for BPSK signals is modified to –3, so the decision threshold for differentiation of BPSK and adjacent QPSK signals can be adjusted to the new value of –2. For $K = 10$, the theoretically expected value for BPSK signals is modified to –11, so the decision threshold for differentiation of BPSK and adjacent QPSK signals can be adjusted to the new value of –6.

4. AMC Algorithms in Multipath Channel with Fading

The problem of AMC in multipath environments is challenging and complex. To be able to solve real-world AMC problems, evaluation of performance of AMC algorithms should include analysis of modulation recognition process in scenario with more realistic environments, not AWGN only.

Constellation	$K = 1$	$K = 2$	$K = 10$
BPSK	–2.000	–3.000	–11.000
QPSK	–1.000	–1.000	–1.000
16-QAM	–0.680	–0.680	–0.680
64-QAM	–0.619	–0.619	–0.619

Tab. 1. Theoretical values of the normalized fourth-order cumulant in terms of coefficient K.

Along with degradation due to AWGN, the transmitted signals are often exposed to fading due to multipath propagation effects. Propagation channel is described as Rayleigh multipath fading channel and modelled in form of a filter with finite impulse response of length L and coefficients $h(k)$, $k = 0, 1, 2,\dots, L-1$. It should be noted that channel impulse response is not treated as ideal. The received signal is obtained as a sum of a linear convolution between transmitted signal $x(n)$ and channel impulse response $h(k)$, and AWGN noise [3] as:

$$y(n) = \sum_{k=0}^{L-1} h(k)x(n-k) + g(n)\ . \tag{10}$$

To estimate correct values of cumulants in these circumstances, propagation channel impact must be taken into consideration. It is quantified through the channel compensation coefficient β [29], [30] as follows:

$$\beta = \frac{\sum_{k=0}^{L-1} \left|h(k)\right|^4}{(\sum_{k=0}^{L-1} \left|h(k)\right|^2)^2}\ . \tag{11}$$

The scaling of cumulants values with coefficient β is done with purpose to compensate channel effects. It should be noted that for determination of coefficient β from (11), it is assumed channel impulse response is a priori known. In this scenario, determination of the normalized fourth-order cumulants for multipath propagation channel is finally obtained as [28]:

$$\hat{C}_{42,\mathrm{x}} = \frac{1}{\beta}\frac{C_{42,\mathrm{y}}}{(\mathrm{C}_{21,\mathrm{y}} - \sigma_{\mathrm{g}}^2)^2}\ . \tag{12}$$

In practice, real working conditions do not imply knowledge of channel impulse response on the receiving side. In such circumstances, it is necessary to estimate all the relevant parameters based on the received signals. It is of interest to test AMC performance in a more realistic propagation scenario. Therefore, environment with unknown channel impulse response was further considered. In this case, CR channel coefficients and channel compensation coefficient β must be estimated based on the received signal $y(n)$. It is done by using HOS elements, as it was shown in [30]. This approach is much less complex comparing to different types of equalizers (either customized for signals modulated according to the modulation formats of interest, either constant modulus algorithm (CMA) and multimodulus algorithm (MMA) equalizers) for multipath propagation compensation. Therefore, this approach is particularly interesting from the aspect of simplicity during the practical implementation of AMC algorithms, as well as from the aspect of economy in terms of occupying the resources necessary for implementation.

The detailed derivation of the formulas is shown in

[30]. For this purpose, the approach with fourth order moments m_c^4 of the received signal for lags denoted as τ, ρ and θ respectively, was used [28–30] as:

$$m_c^4(\tau,\rho,\theta) = E\left[y(n)y(n+\tau)y(n+\rho)y(n+\theta)\right]. \quad (13)$$

Lags $L-1$, $L-1$, k represent values τ, ρ, θ respectively in moments definition [30], and by replacing it in (13), it is obtained:

$$m_c^4(L-1,L-1,k) = E\left[y(n)y(n+L-1)y(n+L-1)y(n+k)\right] \quad (14)$$

where $k = 0, 1, \ldots, L-1$. Further, for these lags it can be shown that the next relation is valid:

$$m_c^4(L-1,L-1,k) = E(x^4)h(0)h(L-1)h(L-1)h(k). \quad (15)$$

According to the moment value m_c^4 for $k = 0$, the following relation is established:

$$m_c^4(L-1,L-1,0) = E(x^4)h(0)h(L-1)h(L-1)h(0). \quad (16)$$

Finally, the normalized channel coefficients $\hat{h}(k)$ can be determined as:

$$\hat{h}(k) = \frac{h(k)}{h(0)} = \frac{m_c^4(L-1,L-1,k)}{m_c^4(L-1,L-1,0)}. \quad (17)$$

Channel coefficients are estimated by replacing $h(k)$ in (11) with $\hat{h}(k)$, and then by using (12) correct fourth-order cumulants value can be expected. It is evident the exceptional simplicity of AMC algorithms based on HOC values, even in the case of multipath propagation channels with unknown impulse response (if as the method for estimation and channel impact compensation, the above-described method with the fourth-order moments of the received signal is applied).

Finally, as a summary, considering these estimated cumulants values and comparing it with predefined thresholds based on Tab. 1, AMC process can be implemented under a real-world communication channel with unknown impulse response. In case of multipath channel with a priori known impulse response, modulation recognition is done by comparing the estimated cumulants values from (12) with the predefined thresholds based on Tab. 1. It should be noted, that channel compensation coefficient β is calculated from (11), but in case of a channel with known impulse response, channel coefficients are known and estimation by usage of (13–17) is not needed. For AWGN only channel, modulation process consists of comparing values obtained from (7) with the predefined thresholds based on values from Tab. 1. It is considered noise variance is known. To the best of our knowledge, this is the first analysis of AMC performance for algorithms based on exploitation of artificial bias induction in standard fourth-order cumulants in propagation conditions including AWGN and multipath propagation channel, both with known and unknown channel impulse response.

5. Performance Evaluation

The transmitted signals are modelled in a form of complex (QPSK, 16-QAM, 64-QAM) and real (BPSK) signal constellations. The random selection of each modulation format occurs with equal probability. The transmitted signals are corrupted by noise, which is modelled as AWGN, with variance consider to be known. In addition, multipath propagation channel (Rayleigh fading channel model), represented in a form of a filter with finite impulse response, is considered as well, both with known and unknown impulse response. Finally, modulated symbols are processed and classified by using different fourth-order cumulants based AMC algorithms.

For the conducted simulations overall sample size N was 2000 symbols. One way to control the overall performance of AMC algorithms, which therefore vary depending on the channel conditions, is to use a larger sample length N during the classification process. The selected sample size should enable robustness of the observed AMC algorithms to the reduction of the SNR value in the system, but additional improvement and performance robustness is obtained with increasing of the sample size. Therefore, how to balance the algorithm model complexity and sample size is also a worthy research direction to design more accurate and efficient models.

Multipath channel with known impulse response is modelled as dispersive channel of length $L = 2$ with known channel coefficients: $h_0 = 1 - i \cdot 0.5$ and $h_1 = 0.6 - i \cdot 0.3$. A "two path" channel model was used for reasons of simplicity. However, results are of a general importance, as the same procedure of determination of channel impact coefficient would be applied and for channels with known impulse response with larger number of paths ($L > 2$). Dispersive channel model coefficients were selected to enable offsets in values for fourth-order cumulants of BPSK signals. For a fair comparison with previously published algorithms and their reported performance, identical parameters were used in the evaluation. Even if channel compensation coefficient β is known, channel impact cannot be compensated and offset is present, what creates difference between theoretically expected and obtained values of cumulants of BPSK signals.

A multipath channel with an unknown impulse response is modelled as the Rayleigh fading channel. The change in channel impulse response over time is an important practical aspect. It is of interest to test the robustness of the AMC algorithms to these changes, because it provides an important information about the potential for practical implementation of the AMC algorithms. Therefore, the channel coefficients were generated as random variables during numerous experiments. The channel coefficient is formed in the following way: $h(0) = 1$, while other coefficients $h(i)$, $i = 1, 2, \ldots, L-1$ are generated as zero mean mutually independent complex Gaussian random variables with variance $\sigma = 0.05$ [30]. The channel length was chosen as $L = 4$.

The proposed AMC algorithms based on artificial bias induction in standard fourth-order cumulants, for both considered test scenarios, $K = 2$ and $K = 10$, were tested along with AMC algorithm based on standard fourth-order cumulant formula ($K = 1$), for the reasons of comparison. Due to artificial bias induction, theoretical expected values of fourth-order cumulants of BPSK signals are modified.

Therefore, in addition it was of interest to conduct analysis of AMC performance of the proposed algorithms with modified thresholds for differentiation of BPSK and QPSK signals according to new theoretical expected values of cumulants of BPSK signals (–2 and –6 for $K = 2$ and $K = 10$, respectively). Performance evaluation of AMC algorithms was done by comparing the obtained P_{cc} values during conducted simulations, for the same real and complex constellations simultaneously, under different considered channel environments for SNR range {–10, +10} dB. Thanks to inducted bias in estimated cumulants, better diffentiation of BPSK signals from complex signals is enabled, and overall AMC performance is improved. That is why for each of propagation scenarios probability values were shown for two cases – for successful classification of BPSK signals only and for all the considered real and complex signals. Presented performance evaluation was carried out through 2000 Monte Carlo simulations, implemented in MATLAB software [31]. For reproducible research, all simulations code is open for considerations and use of other researchers, and can be found at [32].

5.1 AWGN Channel

The P_{cc} values for algorithms based on standard and modified (with artificial bias induction) fourth-order cumulants for different values of bias coefficient K, as well as for algorithms with accordingly adjusted thresholds between BPSK and QPSK signals, were estimated in a wide range of SNR values [–10 to +10 dB]. The results for classification of BPSK signals only and for all considered real and complex signals are shown in Fig. 1 and Fig. 2, respectively.

It is obvious from Fig. 1 that always present offset in cumulants estimates for real signals (BPSK), additionally amplified with artificial bias induction, is directly causing significantly better performance in recognition of BPSK modulation format. All the novelly proposed algorithms have perfect accuracy and have demonstrated maximal AMC performance, without making a single classification error. From that reason, corresponding color curves related to these algorithms in Fig. 1 are overlapping, but only pink color is seen as it is visually dominant over the other colors. The difference in results comparing with standard cumulants based algorithm is from 45% for low SNR zones, then it is reducing while SNR is increasing, until results converged for SNR = 2 dB approximately. Advantage achieved for BPSK signals classification has positive impact in better results for total P_{cc} values when all real and complex signals are observed, and results are improved for approximately 20% in low SNR zones and around 10% for the zones with higher SNR value.

5.2 Multipath Channel with Known Impulse Response and AWGN

A multipath channel is modelled as a dispersive channel, with known channel coefficients. Simulations for performance evaluations are conducted in the same manner as for AWGN channel. The P_{cc} results for successful recognition of BPSK signals and for all the considered real and complex signals' constellations are illustrated in Fig. 3 and

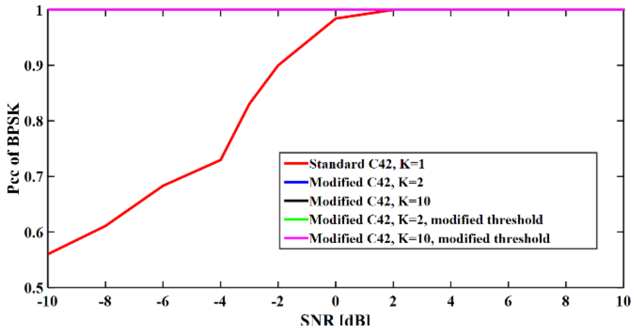

Fig. 1. P_{cc} of BSPK signals for different fourth-order cumulants based AMC vs. SNR in AWGN channel.

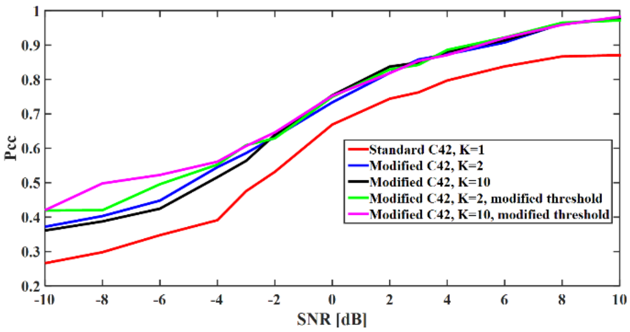

Fig. 2. P_{cc} for different fourth-order cumulants based AMC vs. SNR in AWGN channel.

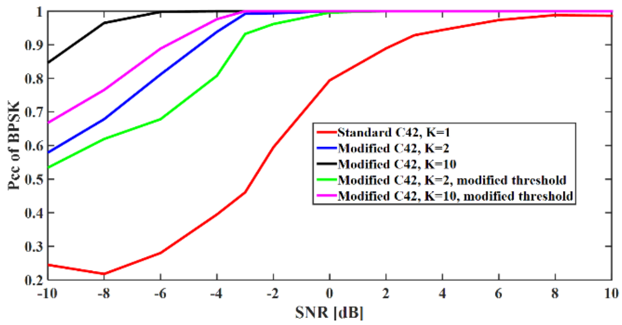

Fig. 3. P_{cc} of BPSK signals for different fourth-order cumulants based AMC vs. SNR in a multipath channel with a known impulse response.

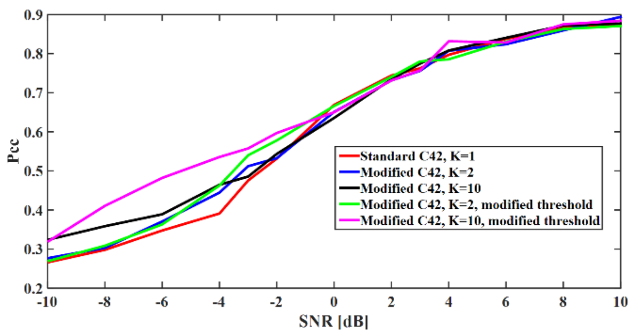

Fig. 4. P_{cc} for different fourth-order cumulants based AMC vs. SNR in a multipath channel with a known impulse response.

Fig. 4, respectively. Obviously, the impact of multiple propagation implies a significant increase in the variances of the obtained estimates of normalized fourth-order cumulants, which leads to a degradation of the overall performance of the AMC comparing to a channel with AWGN only.

As it is evident from Fig. 3, artificially induced bias is significantly contributing for better recognition of BSPK signals in this propagation channel model. All the proposed algorithms have demonstrated better AMC performance comparing with standard algorithm, in range of approximately 30% to 70% for low SNR zones. Difference is then reduced if SNR is increasing, up to almost equal achieved results for SNR values approximately around 7 dB. If modulation recognition process of all observed real and complex signals is considered, AMC performance of the proposed algorithms is improved for approximately 10–20% for the lower (negative) SNR values, especially for algorithms with a higher value of bias coefficient *K* and an adjusted decision threshold between BPSK and QPSK signals. For positive values of SNR, all tested algorithms achieved results on the approximately same level, with accuracy of 88% for SNR = 10 dB.

5.3 Multipath Channel with Unknown Impulse Response and AWGN

For case of a multipath channel with an unknown impulse response, channel structure was estimated as described in Sec. 4. The same set of simulations was conducted as for previous two propagation channel models, and results were collected under the same SNR conditions. Results for classification of BPSK signals only and for all considered real and complex signals are shown in Fig. 5 and Fig. 6, respectively.

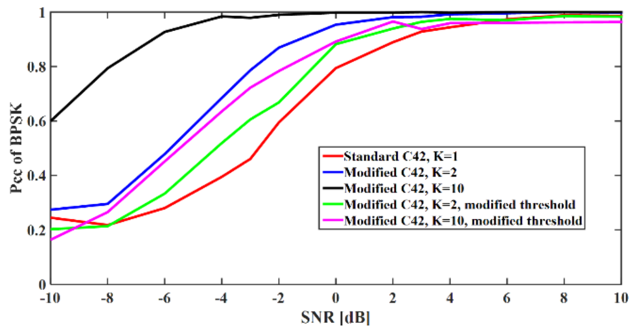

Fig. 5. P_{cc} of BPSK signals for different fourth-order cumulants based AMC vs. SNR in a multipath channel with an unknown impulse response.

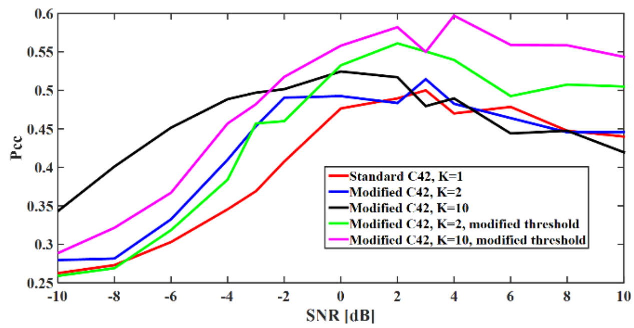

Fig. 6. P_{cc} for different fourth-order cumulants based AMC vs. SNR in a multipath channel with an unknown impulse response.

According to the achieved results illustrated in Fig. 5 and Fig. 6, AMC performance is significantly deteriorated comparing to AWGN and dispersive multipath channel, what is expected due to difficult propagation conditions. Communication channel in a form of a multipath channel with an unknown impulse response causes serious signal degradations. Estimation of unknown channel coefficients cannot enable compensation of channel impact on estimated fourth-order cumulants. All that leads to bigger dispersion of cumulants values and wrong classification decisions. As it can be seen in Fig. 5, classification of BPSK signals for standard AMC algorithm is becoming perfect for values of SNR higher than 3 dB. The other proposed AMC algorithms achieved better results up to 60% depending of SNR value. If the total AMC performance shown in Fig. 6 is analyzed, the novelly proposed algorithms demonstrated superiority and improvements for approximately 10–20% in the whole SNR range, especially the algorithm with a higher value of bias coefficient *K* in zones with SNR < –2 dB, and the algorithm with a higher value of bias coefficient *K* and modified decision threshold for the remaining SNR values.

5.4 Discussion

Generally, it is obvious from Figs. 1–6 that artificial bias induction, done by modification of standard fourth-order cumulant formula, results in higher accuracy of BPSK signals classification and consequently overall AMC performance for the whole considered SNR range for each propagation scenario for all observed real and complex signals' constellations. Also, it was confirmed by conducted simulations that increasing of introduced bias coefficient *K* will result in higher values of P_{cc} and better AMC performance under each observed propagation conditions. That is consequence of better distinguishing of real from complex signals and thus leads to improved modulation recognition process in total. Furthermore, if the decision threshold is adjusted according to the modified theoretical cumulants values, generated by artificial bias induction for BPSK, the total P_{cc} values will be additionally improved for the whole SNR range and for each considered propagation scenario, except for lower SNR zones in multipath channel with unknown

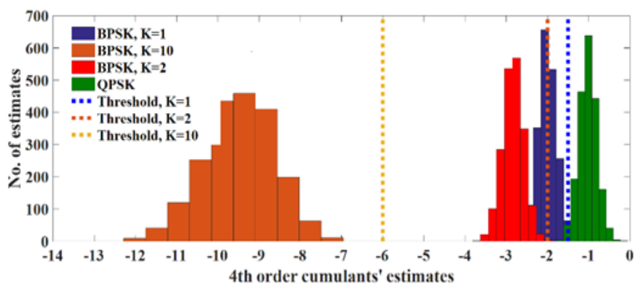

Fig. 7. Resulting histogram of 4th order cumulants' estimates in dispersive channel at SNR = 0 dB, corresponding to QPSK and BPSK signals.

impulse response (SNR < –2 dB). This effect is illustrated in Fig. 7, where resulting histograms of fourth-order cumulants (standard and novelly proposed) values estimated in the channel with a known impulse response (dispersive channel) are presented at SNR = 0 dB.

As it can be noticed from Fig. 7, while cumulants estimates of complex (QPSK) constellation are strictly unbiased, with increasing of coefficient K value low SNR values introduce stronger artificially created bias for BPSK signal's cumulant estimates. This effect represents the reason for the excellent classification performances presented above if using standard threshold value. But, by additional threshold adjustment, distinguishing of BPSK from complex QPSK signals in all simulations scenarios comes with even more superior classification performance comparing to standard threshold value.

If we compare achieved results for different propagation channels, the following can be concluded. As it can be seen from Fig. 2, in AWGN channel novelly proposed algorithms achieved accuracy of 60% approximately for SNR = –3 dB and 97% for SNR = 10 dB, comparing to approximately 60% for SNR = –1 dB and 86% for SNR = 10 dB. Also, it can be noticed that increasing of bias induction coefficient and decision threshold adjustments additionally contribute to AMC performance improvement in lower SNR zones. For multipath channel with known impulse response, as it can be seen from Fig. 4 total classification score is improved in negative SNR zones by using novelly proposed algorithms, while in positive SNR zones results are on similar level for all tested algorithms, with lower accuracy comparing to AWGN, but still high: around 88% for SNR = 10 dB. In a scenario with multipath channel with unknown impulse response P_{cc} results are lower comparing to other two propagation channels. That is expected due to more complex radio environment and bigger signal degradations. Unknown channel coefficients need to be estimated first to be able to compensate channel impact to estimate correct cumulants values. But, even in this case, improvements for P_{cc} can be noticed when using algorithms based on artificial bias induction in fourth-order cumulants. For negative SNR zones, if bias coefficient is larger, classification score is higher. For positive SNR zones algorithms with adjusted thresholds obtained the best results, with accuracy of 55% for SNR = 10 dB comparing to 45% for standard fourth-order cumulant based AMC algorithm.

Another comparison should be made with results achieved in relevant traditional and DL-based AMC algorithms mentioned in Sec. 1. Average performance accuracy for classification of different MPSK and MQAM signals by using HOCs for SNR = 10 dB reported in [24] was around 84.5% for faded channel. Algorithms proposed in this paper demonstrated accuracy of 88% in multipath channel with known impulse response, as shown in Fig. 4, what means performance is enhanced for few percent. In [16], by using new generative feature, performance accuracy of classification of MPSK and MQAM signals of 98.78% was reported in flat fading channel for SNR = 10 dB. Computational complexity is raised in this case due to additional cost required for generation of new feature prior to classification. In [7], authors have shown that the performance accuracy of different Amplitude-Shift Keying (ASK), BPSK, QPSK, and M-QAM classification by using cyclic cumulants is 80%, for SNR = 10 dB. Performance improvement is around 8% comparing to this result in [7]. By using composite deep CNN architecture known as the CDRNN in [17] the recognition accuracy can reach 92.1% for SNR = 18 dB.

Another important aspect for AMC algorithms evaluation is potential for practical implementation. Real-time communications are keen of time where requests need to be processed in very short time. The proposed AMC algorithms is characterized with low computational complexity meaning real-time applications (i.e. intelligent communication receivers, cognitive radio, spectrum sensing, IoT) can benefit of using it. With the rapid development of 5G networks in recent years, the growth of massive IoT devices demands improved communications performance with limited available resources, and thus efficient AMC algorithms are crucially important for the future IoT devices with limited computing and energy resources. The computational order of the proposed fourth-order cumulants based AMC is $O(N)$, while for DL-based algorithms samples are used as input in neural network and extracted feature represents preprocessing step before classification adding to the overall computational costs.

6. Conclusion

Standard cumulants-based AMC algorithms are established as a very representative and wide used. AMC algorithm based on artificial bias induction in fourth-order cumulants is proposed in this paper. Comparative analysis of AMC performance in terms of P_{cc} is done for algorithms based on standard and modified (with artificial bias induction) fourth-order cumulants. By introducing and modification (increasing) of bias coefficient K, which is directly responsible for theoretical expected values of cumulants of BPSK signals, artificial bias is inducted. Therefore, distance between theoretical expected estimates of cumulants of BPSK and adjacent QPSK signal is becoming larger. The goal is to enhance capability to differentiate real and complex signals constellations and thus to improve AMC performance in total. In addition, thresholds for differentiation are adjusted according to the new obtained theoretical values as well, what contributes to better results in modulation recognition process.

According to the conducted evaluation performance tests and achieved numerical results, it can be concluded that the proposed algorithm based on artificial bias induction significantly improves AMC performance, what is a crucial accomplishment of this paper. Superiority is confirmed through bigger P_{cc} values of modulation classification for set of real (BPSK) and complex signal constellations (QPSK, 16-QAM, 64-QAM), over whole considered SNR range for each propagation scenarios, including AWGN and multipath channel with known and unknown impulse response. The remarkable achieved AMC performance enhancements are up to approximately 25%.

The value of introduced bias coefficient K can be subject of optimization to achieve even better results depending of classification accuracy demands for some concrete application. The proposed algorithms enhance AMC performance, but keep low implementation complexity, as well as acceptable computational order, which makes them attractive candidate for practical implementation in real-time applications (cognitive radio, IoT, spectrum sensing, etc.). The computational order of novelly proposed fourth-order cumulants based AMC is still $O(N)$, as it is for standard fourth-order cumulants based AMC algorithm. For DL-based algorithms due to preprocessing before classifications, overall computational costs are increased.

Better channel coefficient estimation results can improve AMC performance for radio environment with multipath propagation in channel with unknown impulse response. Certainly, this should be subject of future research and some advanced SOTA algorithms (based on DL, artificial intelligence, etc.) should be included to enable better estimation of channel coefficients as well as robustness on their changes over time what corresponds to real-world channels. In addition, analysis should be expanded with complex higher order modulation schemes (i.e. 128, 256-QAM), as well as other real signal constellations. AMC algorithm performance testing in other models of multipath channel would be of interest. Comparative AMC performance analysis with other relevant and advanced SOTA AMC algorithms would be of high interest as well.

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