Received May 28, 2020, accepted June 2, 2020, date of publication June 5, 2020, date of current version June 17, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3000358

Modulation Order Reduction Method for Improving the Performance of AMC Algorithm Based on Sixth–Order Cumulants

MARKO S. PAJIC[1], MLADEN VEINOVIC[2], MIROSLAV PERIC[1], (Member, IEEE), AND VLADIMIR D. ORLIC[1], (Member, IEEE)

[1]Vlatacom Institute, 11000 Belgrade, Serbia

[2]Department of Informatics and Computing, Singidunum University, 11000 Belgrade, Serbia

Corresponding author: Vladimir D. Orlic (vladimir.orlic@vlatacom.com)

ABSTRACT For the last two decades a large number of different automatic modulation classification (AMC) algorithms were developed, and many improvements in classification performance are reported. This was commonly achieved by engaging complex structures of neural networks, or other adaptable mechanisms for achieving better precision, when it comes to decision–making. Still, from practical implementation point of view, low algorithm complexity, economical usage of resources and fast execution remain to represent very desirable properties of an AMC algorithm. These properties are recognized in AMC algorithms based on higher - order cumulants as classification features, so their further improvement is of interest. Previous performance analysis of an algorithm based on sixth – order cumulants, in scenarios with complex valued signals' classification, showed that improvements are possible in the context of resources engaged and speed of execution. In this paper a novel approach is presented, for improving the correctness of classification process with sixth–order cumulants and simple two–step feature extraction structure, by engaging a new method for reduction of observed signal's modulation order which directly improves the classification performance. While tested with sixth–order cumulants, proposed method preserves good statistical properties of signal's higher - order cumulants in general, so it can be adopted in other AMC algorithms as well. Proposed modulation order reduction method is described in details, tested through computer simulations within the sixth–order cumulant AMC algorithm, and achieved improvements in performance are presented and explained.

INDEX TERMS Automatic modulation classification, cumulants, feature extraction, higher order statistics, modulation order, noise.

I. INTRODUCTION

Automatic modulation classification (AMC) represents an important integral component of modern wireless systems, crucial for both military and civilian applications. While in military applications it's commonly used for reconstruction of intercepted signals in electronic warfare, its significance for civilian communication grows with dynamic development of software defined radio, smart reconfigurable transceivers and internet of things (IoT) applications, for demodulation of *a priori* unknown signals [1]–[3].

For the last two decades, a large number of various AMC algorithms were developed: both likelihood-based (LB) and feature-based (FB) methods were considered by authors. While the former can lead to optimal solutions at the price of high computations, the latter when properly designed can show performance close to optimal, with significantly reduced computational complexity [4]. FB algorithms based on various instantaneous features, wavelet transforms, higher order statistics–moments and cumulants, or cyclic statistics, are in recent researches commonly supported with complex classifiers which may result in excellent performance, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Deep Neural Networks (DNN) or other Deep-Learning (DL) methods. While

The associate editor coordinating the review of this manuscript and approving it for publication was Aysegul Ucar.

improving the classification performance, these approaches introduce significant complexity in FB algorithms, whose main advantage was always found in their simplicity, at the first place. Additionally, many modern algorithms perform extraction of a number of different features simultaneously ([3], [5], [6]), which makes additional impact on overall complexity.

On the other hand, it was shown that simple AMC algorithms based on cumulants as features of interest, like fourth–order cumulants [7] or sixth–order cumulants [8] only, perform well even under the real – world communication conditions like the fading channel [9]. While being characterized with very low complexity [10], even after many years of research in the field of AMC these algorithms are still considered as the-state-of-the-art of AMC [11]. Moreover, sixth–order cumulants showed significantly better performance than fourth–order cumulants, in this context [12].

Having in mind considerations given above, it is of interest to investigate possibilities for additional improvement of performance of standard algorithm based on sixth–order cumulants. When compared with other up-to-date AMC algorithms, the one based on sixth–order cumulants shows to be superior in low complexity (number of additions and multiplications smaller for several orders of magnitude in comparison with competition, without any exponential and logarithmic operations), memory requirements and inference time. Analysis described in [13], with the sample size N and modulation pool size M in an AMC test, showed that algorithm based on sixth–order cumulants requires $6N$ additions, $16N$ multiplications, M comparisons and $3M$ memory units, in total. Its inference time on i7-6700 CPU is 0.00036s. The same analysis shows that algorithm based on Convolutional Neural Network (CNN) [14], under the same conditions, requires approximately 100 times more additions and multiplications, 100,000 times more comparisons and 1,000 times bigger memory resources. Inference time of CNN-based algorithm, on the same i7-6700 CPU, is 0.00132s. Still, sixth-order cumulants algorithm's performance requires some improvement, in order to make it competitive in classification performance as well. One interesting solution for improvement is presented in this paper: from the basic new idea of modulation order reduction in AMC, along with detailed explanation of proposed novel Modulation order reduction method, and results achieved in classification performance improvement verified via computer simulations. Comparison of proposed solution with other AMC algorithms is also provided, with following discussion.

II. AMC ALGORITHM ON THE BASIS OF SIXTH–ORDER CUMULANTS

The received signal sequence $y(n)$, corrupted by AWGN only during propagation, can be represented by:

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

where $x(n)$ stands for transmitted modulated symbols, and $g(n)$ is AWGN with a zero mean and a variance of σ_g^2. For zero-mean random variable x, associated with transmitted data sequence $x(n)$, the second-order cumulant $C_{21,x} = cum(x, x^*)$ is given by:

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

The sixth-order cumulant $C_{63,x} = cum(x, x, x, x^*, x^*, x^*)$ can be expressed as:

$$C_{63,x} = E(|x|^6) - 9E(|x|^4)E(|x|^2) + 12\left|E(x^2)\right|^2 E(|x|^2) + 12E^3(|x|^2), \tag{3}$$

while the self-normalized sixth-order cumulant is defined as:

$$\hat{C}_{63,x} = C_{63,x}/(C_{21,x})^3. \tag{4}$$

We adopt the following relationships between the cumulants of x and the cumulants of y (associated with received sequence $y(n)$):

$$C_{63,y} = C_{63,x}, \tag{5}$$

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

Consequently, we have:

$$\hat{C}_{63,x} = \frac{C_{63,y}}{(C_{21,y} - \sigma_g^2)^3}. \tag{7}$$

The noise power σ_g^2 can be measured at receiving point, while calculation of second-order and sixth-order cumulant of received signal practically comes down on calculation of mean-values over ensemble of collected signal samples, and their further combining. If number of samples is represented with N, equation (7) in practical realization can be rewritten as:

$$\tilde{\hat{C}}_{63,x} = \left[\frac{1}{N}\sum_{n=1}^{N}|y(n)|^6 - 9\left(\frac{1}{N}\sum_{n=1}^{N}|y(n)|^4 \cdot \frac{1}{N}\sum_{n=1}^{N}|y(n)|^2\right) + 12\left(\left|\frac{1}{N}\sum_{n=1}^{N}y^2(n)\right|^2 \cdot \frac{1}{N}\sum_{n=1}^{N}|y(n)|^2\right) + 12\left(\frac{1}{N}\sum_{n=1}^{N}|y(n)|^2\right)^3\right] \cdot \frac{1}{\left(\frac{1}{N}\sum_{n=1}^{N}|y(n)|^2 - \sigma_g^2\right)^3}. \tag{8}$$

In Table 1 the theoretic values of the sixth-order cumulants for some well-adopted modulation constellations are shown. These theoretical values of cumulants represent only expected values of cumulants; some portion of dispersion around expected values is unavoidable in practical calculations. This phenomenon was explored and described in literature for fourth-order cumulants [15], and for sixth-order cumulants [16]. The error variance due to limited precision

TABLE 1. Theoretical sixth–order cumulants of some complex constellations.

Feature	QPSK	16-QAM	64-QAM
$\hat{C}_{63}$	4.000	2.080	1.797

of calculation of $C_{63,x}$, for complex signals with N samples, is given with:

$$
\begin{aligned}
&Nvar(C_{63,x}) \\
&= [m_{12,6} - m_{6,3}^2] + 9[m_{2,1}^2(48m_{4,2}m_{2,1}^2 - 54m_{4,2}^2 \\
&\quad +96m_{2,1}^4 - 64m_{6,3}m_{2,1}) + m_{4,2}(9m_{4,2}^2 + 16m_{6,3}m_{2,1} \\
&\quad -2m_{8,4}) + m_{2,1}(17m_{8,4}m_{2,1} - 2m_{10,5})], \qquad (9)
\end{aligned}
$$

where $m_{k,m} = E[y^{k-m}(y^*)^m]$ represents mixed moment of order k with m conjugations.

As it can be noticed from equation (9), error variances are directly proportional with sample size N, and take different values for different modulation formats [16]. Limited precision in numerical calculations is not the only source of dispersion of higher-order cumulants' values: dispersion is also implicated by unequal number of different symbols in randomly generated messages, and by the presence of the noise.

Decision making process for the modulation recognition is based on comparison of obtained values of estimates $\tilde{\hat{C}}_{63,x}$ with predefined thresholds. In [17] it was shown, on the basis of intensive computer simulations, that optimal comparison threshold values are positioned at the middle of intervals between expected (theoretical) values corresponding with particular modulation formats, following well-known theoretical conditions for minimal error probability [18].

Dispersion of $\tilde{\hat{C}}_{63,x}$ estimates in randomly generated signal, explained through error variance, may lead to incorrect signal classification even in cases when noise impact is negligible. This happens, exactly, with sixth–order cumulant features when distinguishing 16-QAM from 64-QAM signals: as illustrated in Figure 1, where distribution of estimates achieved via Monte-Carlo simulations of described AMC algorithm for 16-QAM and 64-QAM signals, at $SNR = 20$dB, is presented.

As it can be clearly noticed from Figure 1, even at high SNR, some $\tilde{\hat{C}}_{63,x}$ estimates violate the decision threshold (placed at the middle of the interval between theoretical cumulant values, i.e. at $(1.797+2.08)/2 \approx 1.94$), meaning that errorless classification of these QAM signals is not feasible even under very good channel conditions. The same conclusion stands for the fourth-order cumulants used as AMC features in {16-QAM, 64-QAM} scenario.

At the same time, in [17] it was reported that classification of Quadrature Phase-Shift Keying (QPSK) signals, in case where modulation candidates are randomly selected from the set of {QPSK, 16-QAM, 64-QAM} constellations, is very good. QPSK signals' classification is practically errorless

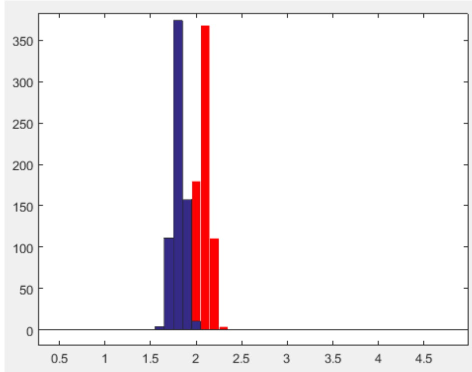

FIGURE 1. Histogram of normalized sixth-order cumulant estimates of 16-QAM (red) and 64-QAM (blue) signals, in Monte-Carlo simulations with AWGN at SNR = 20dB.

at all SNR values higher than 5dB, even with relatively small number of samples N used. This fact opened good space for additional effectiveness in AMC algorithm based on sixth-order cumulants, through simple two-step classification defined in following manner:

- Step 1: estimate $\tilde{\hat{C}}_{63,x}$ value according to equation (8), by using some relatively low number of samples N_1, and compare it with ''middle of the interval'' threshold between QPSK and 16-QAM signal's cumulants (equal to 3.04). If signal is within this step recognized as QPSK, AMC procedure is over;
- Step 2: If estimated $\tilde{\hat{C}}_{63,x}$ value corresponds with QAM signals' values, repeat the procedure from equation (8) with (bigger) number of samples N in order to provide necessary precision in classification of QAM signals, and compare it with ''middle of the interval'' threshold between 64-QAM and 16-QAM signal's cumulants.

This concept is justified when condition $SNR > 5$dB is fulfilled, which can be confirmed through estimation of SNR just before the feature extraction starts [19]. It should be noted here that condition of having $SNR > 5$dB represents an important limiting factor in fair evaluation of proposed algorithm, since below this value no performance improvement should be expected, thus no additional competiveness of AMC algorithm would be achieved. Also, algorithm's performance is strongly dependent on synchronization: the algorithm assumes that symbol rate of received signal sequence $y(n)$ is known *a priori*, and all samples are collected in the perfect synchronization at this rate. Moreover, it also assumes that no phase jitter is present, since it would dramatically damage the concept of cumulants' calculations, leading to a poor classification performance. These considerations should be taken into account for practical implementation of the algorithm, since they're representing crucial limiting factors for AMC algorithm's functionality. Still, under these strong conditions of appropriate synchronization and SNR value, proposed two–step approach in AMC algorithm execution, along with providing opportunity of effective sample size manipulations, now also opens the additional space for investigation of possibilities to further enhance correctness in classification of QAM signals within the Step 2, which would make crucial impact on overall AMC algorithm performance.

III. MODULATION ORDER REDUCTION METHOD FOR QAM SIGNALS

The fact that QPSK signals in AWGN are classified with sixth-order cumulant algorithm quite well (within the Step 1 in described two - step procedure), leads to the following idea for potential enhancement in classification of 16-QAM and 64-QAM signals (within the Step 2): reduction of modulation order of observed QAM signal, by transforming 16-QAM into "QPSK - like" signal and 64-QAM into "16-QAM - like" signal, then followed by further extraction of sixth–order cumulant estimates, just like in the standard approach. This kind of signal transformation would naturally exploit good properties of QPSK signals classification in order to distinguish between different QAM constellations.

To the best of our knowledge, the only work that ever explored the idea of modulation order reduction for the purpose of AMC is the one described in [20]-[21], where authors proposed transformation of M-QAM signal y into the new M'-QAM signal y' by applying absolute value operation on the real part and the imaginary part of the original M-QAM signal:

$$y' = |Re(y)| + j\,|Im(y)|\,, \tag{10}$$

where the modulation order of the new signal is M' = M/4.

While the method described in equation (10) results with reduction of modulation order as expected, some of its deficiencies are obvious. At the first place, new signal is clearly biased, having all the particular samples (i.e. signal symbols after transformation) located in the first quadrant of the complex plane, only. This obviously makes a big impact on the whole mathematical apparatus standing behind the statistical properties of QAM signals, which is basic for the concept of cumulants, given through equations (1)–(9). This kind of deficiency can be resolved with performing additional operations over the signal y', in order to remove DC component in its real and imaginary parts simultaneously. But, this works only with theoretical signal which is not corrupted by the noise. When the noise is involved (and the model considered in this work assumes the presence of AWGN, equation (1)), much more serious issue arises with the method proposed in equation (10): statistical properties of the noisy components are disturbed in drastic manner, and equations (1)–(9) are not valid anymore. The same can be concluded with any other AMC methods which are derived on the basis of statistical properties of AWGN: after transformation in equation (10), statistical properties of AWGN change dramatically and algorithms collapse. This would be the reason why the method proposed in [20], [21] wasn't explored by other authors in significant extent.

In order to preserve statistical properties of both QAM signal and AWGN, along with achieving modulation order reduction, we propose the following method:

1. Select only the samples of observed M-QAM signal with highest energy (corresponding with 1/4 of the total number of modulated symbols); discard all the other samples (corresponding with 3/4 of the total number of modulated symbols, the ones with lower energy). This is done with simple comparators on both real and imaginary part of observed signal, with comparison thresholds set at the value V_{CUT} corresponding with 0.62 of signal's maximum amplitude level.
2. Translate the values of the whole sample set created under point no. 1 in complex plane, by subtracting the value of V_{CUT} from the absolute value of both real and imaginary component of the signal.

This simple procedure results with generation of a new (transformed) signal y', having the clear form of M'-QAM with the modulation order M' = M/4, derived from observed M-QAM signal y. It is unbiased, and all the statistical properties of its AWGN components are preserved, providing that adoption of cumulant–based algorithms is feasible on this signal after transformation.

Execution of described Modulation order reduction method over 16-QAM signal is illustrated on Figure 2 and Figure 3, while resulting "QPSK - like" signal is presented in Figure 4.

Execution of described Modulation order reduction method over 64-QAM signal is illustrated on Figure 5 and Figure 6, while resulting "16-QAM - like" signal is presented in Figure 7.

After modulation order reduction, further processing goes straight–forwardly: values of sixth–order cumulants are estimated over samples generated in modulation order reduction transformation and then compared with standard decision threshold, resulting from the values given in Table 1. As it can be confirmed from Figure 4 and Figure 7, classification of 16-QAM from 64-QAM signals now comes down on distinguishing "QPSK - like" from "16-QAM like", so corresponding decision threshold should be used for reduced constellations.

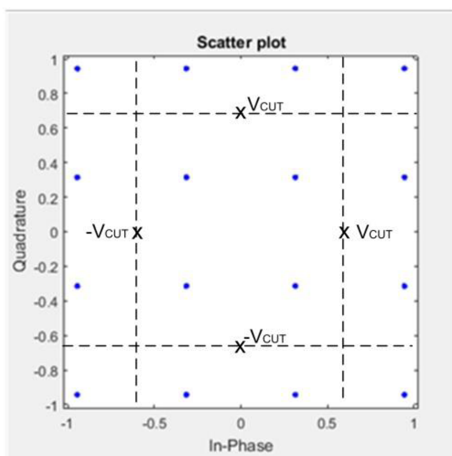

FIGURE 2. Modulation order reduction method adopted on 16-QAM signal, first step: only symbols above the comparison threshold value are selected for further processing.

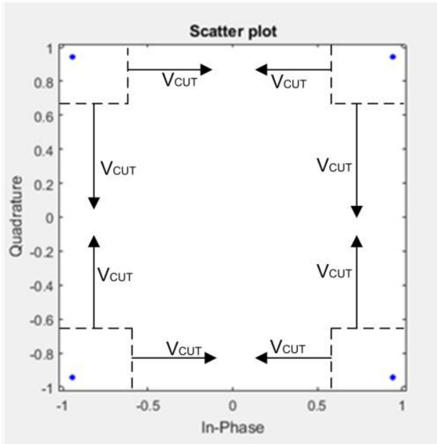

FIGURE 3. Modulation order reduction method adopted on 16-QAM signal, second step: both real and imaginary parts of selected symbols are translated in complex plane for the value of comparison threshold.

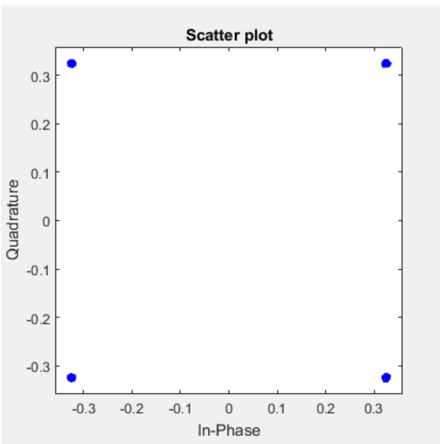

FIGURE 4. Modulation order reduction method adopted on 16-QAM signal, result: resulting signal, "QPSK - like".

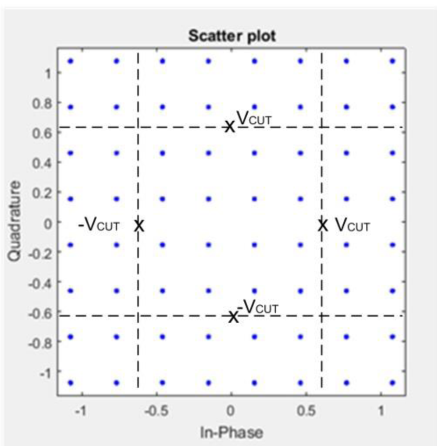

FIGURE 5. Modulation order reduction method adopted on 64-QAM signal, first step: only symbols above the comparison threshold value are selected for further processing.

IV. SIMULATIONS AND PERFORMANCE ANALYSIS

We carried out the simulations through 2,000 Monte-Carlo trials and N received data samples were collected for AMC in each trial, in scenario with modulation candidates considered

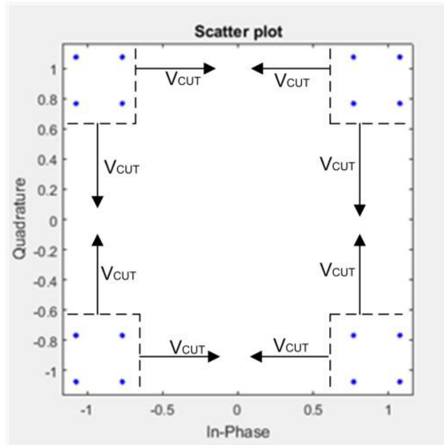

FIGURE 6. Modulation order reduction method adopted on 64-QAM signal, second step: both real and imaginary parts of selected symbols are translated in complex plane for the value of comparison threshold.

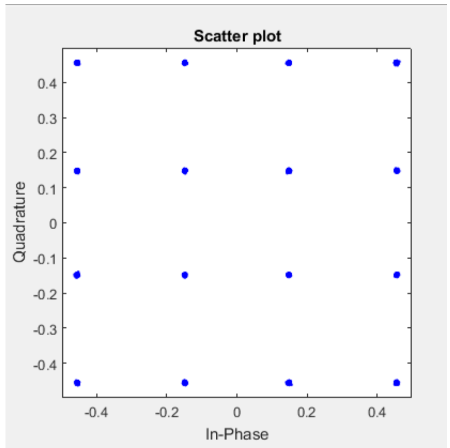

FIGURE 7. Modulation order reduction method adopted on 64-QAM signal, result: resulting signal, "16-QAM - like".

from the set {QPSK, 16-QAM, 64-QAM}. Algorithm with standard $\tilde{\hat{C}}_{63,x}$ features and two-step processing [17] for classification of QPSK signals from $N_1 < N$ samples and classification of QAM signals from all N samples was simulated, along with algorithm based on the same cumulant features, but with Modulation order reduction method (proposed in this paper) involved, in two-step processing procedure presented in Figure 8.

When compared with the structure of standard sixth–order cumulants AMC algorithm, the one presented in Figure 8 differs only in the presence of "Modulation order reduction" block (and correspondingly changed value for comparison when making decision about QAM signal constellation). Thus, the only added complexity comes from the Modulation order reduction method.

In order to provide fair comparison of achieved performance with other comparable algorithms, AMC algorithm based on fourth–order cumulants [7] was simulated as well, under the same set of modulation candidates and sample size $N = 2000$. This value of N was selected in order to match directly with the one used in simulations described in [7], and

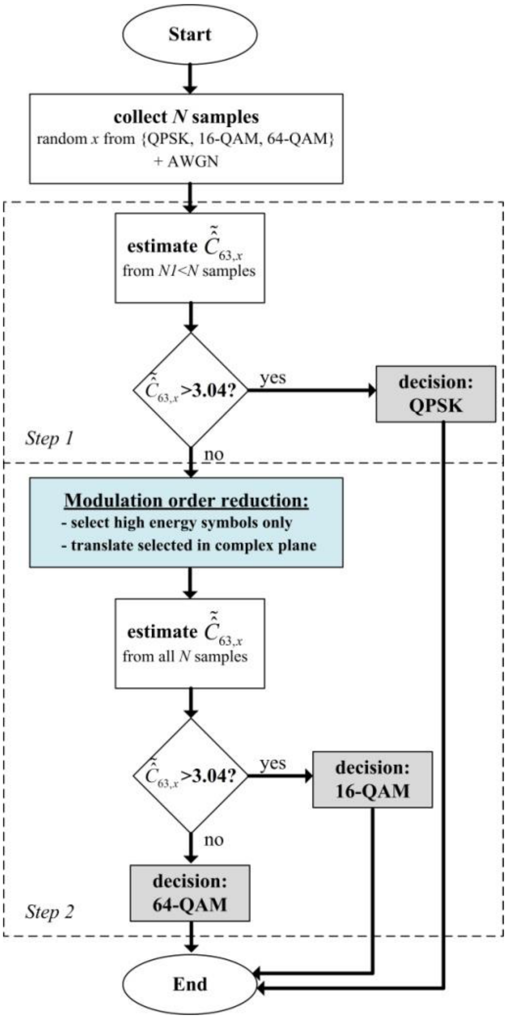

FIGURE 8. Diagram of AMC algorithm based on sixth-order cumulants with Modulation order reduction method, in {QPSK, 16-QAM, 64-QAM} scenario.

represents the main controlling parameter from the aspect of AMC performance. The AWGN channel was simulated with noise power σ_g^2 considered to be known. For each particular *SNR* value, and within every particular Monte-Carlo trial, the same set of N samples was processed by all simulated algorithms, thus providing the fair comparison under the exactly same channel conditions and over the exactly same input data.

Comparison thresholds for standard sixth–order cumulants AMC algorithm and for the algorithm presented in Figure 8 are having the values as previously described in this paper, while comparison thresholds for the algorithm [7] were selected as the ''middle of interval'' values between the theoretical fourth–order cumulants of considered modulation formats.

Correct classification probability P_{CC} was calculated versus *SNR*, and Figure 9 illustrates the results of simulation.

As it can be confirmed from Figure 9, proposed AMC algorithm based on sixth-order cumulants and Modulation order reduction method outperforms both ''classical''

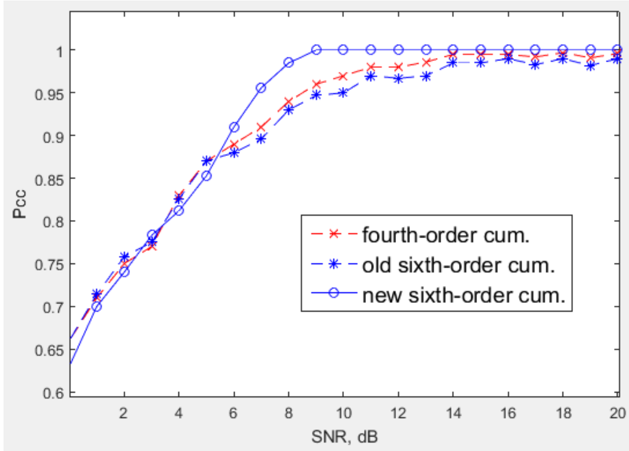

FIGURE 9. Correct classification probability in {QPSK, 16-QAM, 64-QAM} scenario with AWGN channel, N = 2000.

cumulant–based algorithms. While for *SNR* values between 0 and 5dB performance of all considered algorithms is similar (as mentioned earlier, standard $\tilde{\tilde{C}}_{63,x}$ features do not provide errorless classification of QPSK signals at *SNR* being that low, so no resulting improvement with proposed method is achieved here), at $SNR \geq 5$dB novel proposed algorithm results with higher probability of correct classification. Moreover, starting approximately from the $SNR = 9$dB and above, novel algorithm provides errorless classification in considered scenario, which is not feasible with standard cumulants only. Although their performance is quite close to the value of $P_{CC} = 100\%$, as explained in section II of this paper and presented in Figure 1, basic properties of cumulants for higher- order QAM signals simply make appearance of errors in classification unavoidable, even at higher *SNR* values.

Errorless classification of novel AMC algorithm comes directly from proposed Modulation order reduction method. In order to illustrate this statement, we present considered QAM signals at $SNR = 20$dB, along with reduced modulation order signals formed through proposed order reduction method and resulting histogram of their sixth–order cumulants in Figure 10.

From Figure 10 one can easily confirm that, although being relatively low, noise level makes obvious impact on transmitted signal, but Modulation order reduction method still leads to a situation with decision- making under preferable conditions of well–grouped values of extracted features, i.e. sixth–order cumulants, being at the safe distance from decision threshold (i.e. 3.04) and unbiased.

Direct comparison of Figure 10.E) with Figure 1 explains the difference achieved when it comes to decision–making point. With lowering the value of *SNR* further down, variances of resulting sixth–order cumulant features are getting bigger, but the features themselves are still unbiased, which provides continuous errorless classification even slightly below $SNR =$ 10dB. It should be noted that this does not stand in the case of using method [20]-[21]. Only preserving both statistical properties of transmitted signal and noise simultaneously, leads

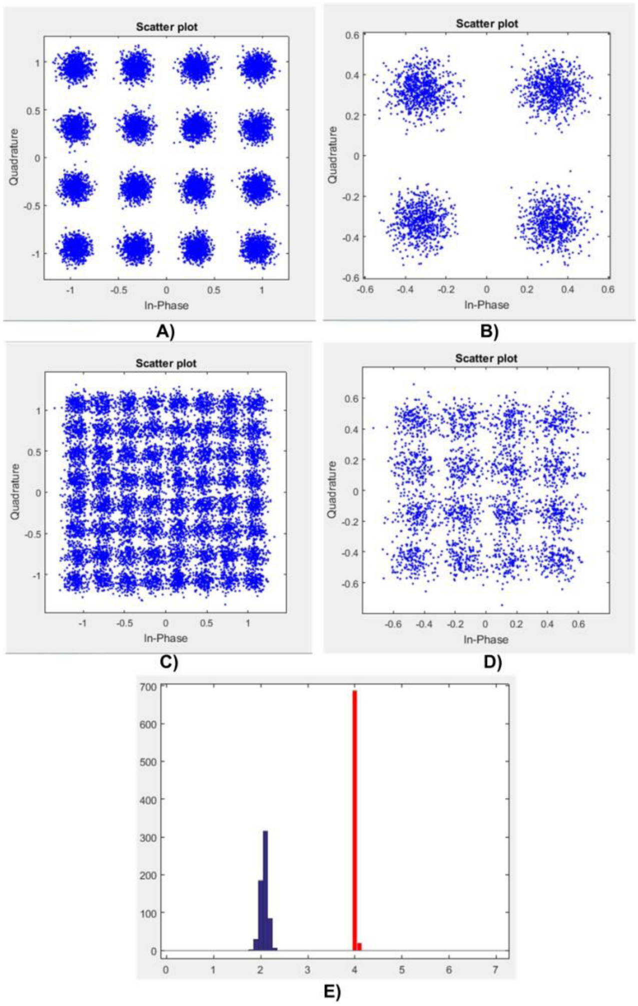

FIGURE 10. AMC with sixth–order cumulants and Modulation order reduction: A) 16-QAM signal at SNR = 20dB, B) 16-QAM transformed into "QPSK - like", C) 64-QAM signal at SNR = 20dB, D) 64-QAM transformed into "16-QAM - like", E) resulting histogram of sixth–order cumulant values estimated in Monte–Carlo trials at SNR = 20dB, corresponding with 16-QAM (red) and 64-QAM (blue) transmitted signal.

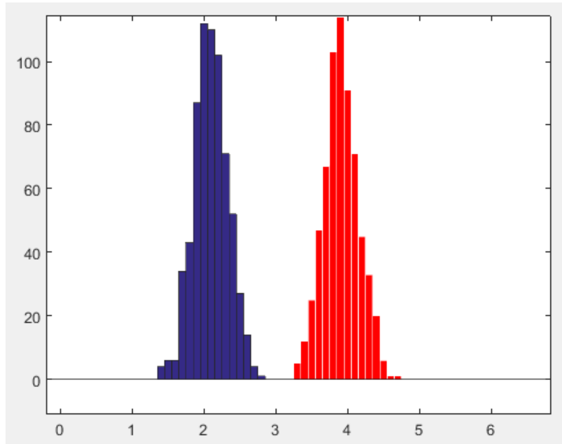

FIGURE 11. Resulting histogram of sixth–order cumulant values estimated in Monte–Carlo trials at SNR = 10dB, corresponding with 16-QAM (red) and 64-QAM (blue) transmitted signal.

to this kind of result. Although the only channel disturbance source considered (and simulated) here is the noise, the nature of cumulants provides that all presented considerations will also stand in the case of flat–fading channel (while for more complex channel models additional channel estimation procedure needs to be introduced in simulated algorithms, [7], [8], [22]). As the final illustration, histogram of sixth–order cumulant estimates for QAM signals achieved with novel method of Modulation order reduction at $SNR = 10$dB is presented in Figure 11.

The reason of described classification performance improvement lies in numerical values of error variances, calculated from equation (9) (and corresponding with particular signal constellations), along with numerical values of distance between particular higher - order cumulants (for the same constellations). As it was described in [8], the ratio of standard deviation (i.e. square root of $var(C_{63,x})$, given by equation (9)) and the distance between $\hat{C}_{63}$ values (given in Table 1) is used to describe the efficiency of cumulant–based algorithm in distinguishing one signal constellation from another. Numerical values of this ratio presented in [8], in the case of sixth–order cumulants, are approximately 5 times lower in distinguishing QPSK from 16-QAM signals than in the case of distinguishing 16-QAM from 64-QAM signals. While this explains good QPSK classification performance with standard sixth–order cumulants in general, at the same time it represents the explanation of improvement in QAM signals' classification achieved with proposed Modulation order reduction method: transformed signals are characterized with approximately 5 times lower ratio of standard deviation and distance between their $\hat{C}_{63}$ values, in comparison with signals before transformation, which leads directly to classification improvement, as demonstrated in presented simulations. The same ratio for signals transformed with proposed Modulation order reduction method is approximately 4 times lower than the one calculated in case of fourth–order cumulants (without order reduction), which is further leading to the same conclusion as given above, and again corresponding with presented simulation results very closely.

Complexity of simulated AMC algorithms represents another perspective for mutual comparison. Achieved performance improvement with proposed Modulation order reduction method comes at the cost of increased complexity: this concept directly introduces $2N$ additional comparisons and $2N$ additions, when compared with standard sixth–order cumulants AMC algorithm. While the total number of additions does not change significantly in this way (it stays in the same order of magnitude), the increase in total number of comparisons necessary for algorithm execution is significant. Still, it remains relatively low, in comparison with other nowadays actual algorithms: for example, from [13] it can be concluded that even with increased number of comparisons (i.e. the Modulation order reduction method involved), algorithm proposed in this paper still has approximately 10 times less comparisons than CNN-based algorithm [14], whose number of additions remains approximately 100 times bigger, and which is still characterized with the presence of exponentials and bigger demands in memory resources, which is all finally leading to a longer inference time.

It should be also noted that described Modulation order reduction method can be combined further with other techniques for additional improvement of AMC algorithm performance. For example, as reported in [22], bigger sample size N and averaging may lead to a better classification performance. Using a bigger initial sample size is effectively absorbed with savings achieved in economical classification of QPSK signals with smaller number of samples, as proposed in two–step AMC procedure. What is even more important, described Method for modulation order reduction is completely independent from the feature extraction mechanism observed in this paper. It could be used with success not only with sixth–order cumulants, but also with fourth–order cumulants [7], eighth–order cumulants [23], or any combination of cumulant features, which are all very popular in modern research. Obviously, it can be also expanded further with more complex classifiers, in those applications where introducing more significant overall computational complexity is acceptable, but those considerations are out of scope of this work.

V. CONCLUSION

In this paper a novel approach for improving the correctness of classification process in AMC algorithm based on sixth–order cumulants and simple two–step feature extraction structure is presented, by engaging a new method for reduction of observed signal's modulation order. Proposed modulation order reduction method is described in details, tested through computer simulations within the sixth–order cumulant AMC algorithm, and compared with standard AMC algorithms (without modulation order reduction), based on sixth–order and fourth–order cumulants. Achieved improvements in performance are presented and explained. Errorless classification of QAM signals at higher SNR values and more efficient classification when compared with classical algorithms, showed that Modulation order reduction method proposed in this paper directly improves the classification performance. While tested with sixth–order cumulants as features of interest, proposed method preserves good statistical properties of signal's higher order cumulants in general, so it can be adopted in other AMC algorithms as well. Described improvements are coming at the cost of (some) added complexity: in comparison with standard sixth–order cumulants AMC algorithm, Modulation order reduction method itself introduces additional comparisons and complex additions for classification of QAM signals. Classification of QPSK signals is carried out in absolutely the same manner as in standard AMC algorithm, without additional complexity. Still, even with this added complexity taken into account, overall characteristics described through the total number of additions and multiplications, absence of any exponential and logarithmic operations, memory requirements and CPU inference time, show to be smaller for several orders of magnitude in comparison with competition. This makes achieved improvements of AMC algorithm performance, which provided necessary competitiveness, more than justified. At the same time, this makes proposed Modulation order reduction method a very attractive for future research in exploring potential performance improvements under the more demanding propagation conditions (like multipath, interference, and other). Apart from the AMC framework considered in this paper, potentials in integrating proposed Modulation order reduction method within other AMC algorithms and/or more sophisticated classifiers (like ANN, SVM, DL and other) seem to be very promising.

REFERENCES

[1] Y. A. Eldemerdash, O. A. Dobre, and M. Öner, "Signal identification for multiple-antenna wireless systems: Achievements and challenges," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 3, pp. 1524–1551, 3rd Quart., 2016.

[2] D. H. Al-Nuaimi, I. A. Hashim, I. S. Z. Abidin, L. B. Salman, and N. A. M. Isa, "Performance of feature-based techniques for automatic digital modulation recognition and classification—A review," *Electronics*, vol. 8, no. 12, p. 1407, Nov. 2019.

[3] T. Zhang, C. Shuai, and Y. Zhou, "Deep learning for robust automatic modulation recognition method for IoT applications," *IEEE Access*, early access, Mar. 16, 2020, doi: 10.1109/ACCESS.2020.2981130.

[4] A. Hazza, M. Shoaib, S. A. Alshebeili, and A. Fahad, "An overview of feature-based methods for digital modulation classification," in *Proc. 1st Int. Conf. Commun., Signal Process., Appl. (ICCSPA)*, Feb. 2013, pp. 1–6.

[5] J. Lee, J. Kim, B. Kim, D. Yoon, and J. Choi, "Robust automatic modulation classification technique for fading channels via deep neural network," *Entropy*, vol. 19, no. 9, p. 454, Aug. 2017.

[6] A. K. Ali and E. Erçelebi, "An M-QAM signal modulation recognition algorithm in AWGN channel," *Sci. Program.*, vol. 2019, pp. 1–17, May 2019.

[7] H.-C. Wu, M. Saquib, and Z. Yun, "Novel automatic modulation classification using cumulant features for communications via multipath channels," *IEEE Trans. Wireless Commun.*, vol. 7, no. 8, pp. 3098–3105, Aug. 2008.

[8] V. D. Orlić and M. L. Dukić, "Automatic modulation classification algorithm using higher-order cumulants under real-world channel conditions," *IEEE Commun. Lett.*, vol. 13, no. 12, pp. 917–919, Dec. 2009.

[9] S. Majhi, R. Gupta, W. Xiang, and S. Glisic, "Hierarchical hypothesis and feature-based blind modulation classification for linearly modulated signals," *IEEE Trans. Veh. Technol.*, vol. 66, no. 12, pp. 11057–11069, Dec. 2017.

[10] L. Han, F. Gao, Z. Li, and O. A. Dobre, "Low complexity automatic modulation classification based on order-statistics," *IEEE Trans. Wireless Commun.*, vol. 16, no. 1, pp. 400–411, Jan. 2017.

[11] A. A. Pennacchio, J. P. C. L. da Costa, V. M. Bordini, G. del Gado, and S. M. L. da Silva, "Eigenfilter-based automatic modulation classification with offsets for distributed antenna systems," in *Proc. 34th Simposio Brasilerio Telecomunicacoes Processamento Sinais*, 2016, pp. 260–261.

[12] X. Li, F. Dong, S. Zhang, and W. Guo, "A survey on deep learning techniques in wireless signal recognition," *Wireless Commun. Mobile Comput.*, vol. 2019, pp. 1–12, Feb. 2019.

[13] C.-F. Teng, C.-Y. Chou, C.-H. Chen, and A.-Y. Wu, "Accumulated polar feature-based deep learning for efficient and lightweight automatic modulation classification with channel compensation mechanism," 2020, *arXiv:2001.01395*. [Online]. Available: http://arxiv.org/abs/2001.01395

[14] S. Peng, H. Jiang, H. Wang, H. Alwageed, and Y.-D. Yao, "Modulation classification using convolutional neural network based deep learning model," in *Proc. 26th Wireless Opt. Commun. Conf. (WOCC)*, Newark, NJ, USA, Apr. 2017, pp. 1–5.

[15] A. Swami and B. M. Sadler, "Hierarchical digital modulation classification using cumulants," *IEEE Trans. Commun.*, vol. 48, no. 3, pp. 416–429, Mar. 2000.

[16] V. D. Orlić and M. L. Dukić, "Properties of an algorithm for automatic modulation classification based on sixth-order cumulants," in *Proc. ICEST Conf.*, Veliko Tarnovo, Bulgaria, 2009, pp. 635–638.

[17] V. D. Orlić and M. L. Dukić, "Setting the optimal decision threshold and analysis of impact of sample size on automatic modulation classification based on sixth-order cumulants," in *Proc. Int. Sci. Conf. Defensive Technol. OTEH*, Belgrade, Serbia, 2012, pp. 511–515.
[18] A. B. Carlson, P. B. Crilly, and J. C. Rutledge, *Communication Systems*, 4th ed. New York, NY, USA: McGraw-Hill, 2002.
[19] Z. Wu, S. Zhou, Z. Yin, B. Ma, and Z. Yang, "Robust automatic modulation classification under varying noise conditions," *IEEE Access*, vol. 5, pp. 19733–19741, 2017.
[20] W. Chen and S. Yang, "Recursive classification of MQAM signals based on higher order cumulants," *J. Electron. China*, vol. 19, no. 3, pp. 270–275, Jul. 2002.
[21] L. Yang, Z. Ji, X. Xu, X. Dai, and P. Xu, "Modulation classification in multipath fading environments," in *Proc. 4th Int. Symp. Wireless Commun. Syst.*, Oct. 2007, pp. 171–174.
[22] V. D. Orlić and M. L. Dukić, "Automatic modulation classification: Sixth-order cumulant features as a solution for real-world challenges," in *Proc. 20th Telecommun. Forum (TELFOR)*, Nov. 2012, pp. 392–399.
[23] L. Liu and J. Xu, "A novel modulation classification method based on high order cumulants," in *Proc. Int. Conf. Wireless Commun., Netw. Mobile Comput.*, Sep. 2006, pp. 1–5.

MARKO S. PAJIC received the B.Sc. and M.Sc. degrees from the School of Electrical Engineering, University of Belgrade, Serbia, in 2007 and 2010, respectively. He is currently pursuing the Ph.D. degree with Singidunum University, Belgrade, Serbia.

He currently works as a Senior System Engineer and a Research Trainee with the Vlatacom Institute of High Technologies, Belgrade. His research interests include radio communication systems, security systems, radar systems, and system design.

MLADEN VEINOVIC received the B.Sc., M.Sc., and Ph.D. degrees from the Faculty of Electrical Engineering, University of Belgrade, Serbia, in 1986, 1990, and 1996, respectively.

In 1987, he was employed at the Institute of Applied Mathematics and Electrical Engineering, Belgrade. He has been serving as the Head of the Department for the development of special purpose devices in telecommunication systems. In 2005, he started working with the Faculty of Informatics and Computing, Singidunum University. He is the author of many scientific articles in the field of security in communication systems. His research interests include data security, computer networks, data bases, and digital signal processing.

MIROSLAV PERIC (Member, IEEE) received the Dipl.Eng. and M.Sc. degrees from the School of Electrical Engineering, University of Belgrade, Serbia, in 1993 and 2004, respectively, and the Ph.D. degree from the Faculty of Technical Sciences, University of Novi Sad, Serbia, in 2013.

He is currently the Chief Technology Officer with the Vlatacom Institute of High Technologies, Belgrade, Serbia. His research interests include system design, signal processing, electro-optics systems, radar systems, radio and fiber optics communication networks engineering, and performance measurement and optimization.

VLADIMIR D. ORLIC (Member, IEEE) received the B.S. and Ph.D. degrees in electrical engineering from the University of Belgrade, Serbia, in 2007 and 2011, respectively.

He currently works as a Systems Architect with the Vlatacom Institute, Belgrade, Serbia, responsible for project management in domain of surveillance systems, along with scientific and development research. He has the formal title of the Scientific Associate. His research interests include communication systems, digital and analog signal processing, algorithm development, security systems, and radio communications.