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STATISTICAL ANALYSIS OF THE IMPACT OF LOSSY COMPRESSION ALGORITHMS ON THE STRUCTURE OF DIGITAL IMAGES

This paper investigates the impact of lossy compression algorithms on the statistical structure of digital images. Compression is a necessary step in data storage and transmission, but it changes the original characteristics of the signal, which can complicate further analysis in computer vision, remote sensing, and medical diagnostics. Traditional quality metrics (MSE, PSNR, SSIM) do not fully reflect these statistical changes, so the analysis of histograms and moments of distortion distribution is relevant. The aim of this study is to quantitatively assess the impact of JPEG, JPEG2000, WebP, and AVIF codecs on the stochastic properties of images. For this purpose, two types of data were used: a synthetic test image with a well-defined structure and a real image with natural textural inhomogeneities. Both images were compressed at different quality parameters (Q = 30, 50, 70, 90). Subsequent analysis included constructing histograms of the difference images and calculating the mean, standard deviation, skewness, and kurtosis, as well as checking the spatial consistency of the distortions. The obtained results showed that for the codecs under study, a decrease in the quality parameter Q leads to an increase in variance and kurtosis, while the values of the mean and asymmetry remain close to zero. For the synthesized image, JPEG2000 produces the largest variation in stochastic characteristics, while WebP and AVIF produce the smallest, with AVIF generating very narrow distributions with high kurtosis. At the same time, for the real compressed image, there is an overall decrease in the standard deviation and kurtosis values compared to the synthetic case, and the heavy-tailed distributions typical of AVIF and WebP on the test data are less pronounced. This can be explained by the presence of natural textures, over which compression errors are more evenly distributed. The study of spatial dependencies confirmed the local nature of the distortions, without significant correlation between the rows of the difference images. The analysis results show that different formats affect the statistical properties of images in different ways. The use of both synthetic and real images made it possible to demonstrate the differences between limiting scenarios and practical conditions of using the codecs under study. The results can be used to improve methods for evaluating compression quality and to develop efficient procedures for automated processing and statistical classification of images.

Keywords: *image compression, JPEG, JPEG2000, WebP, AVIF, statistical analysis.*

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СТАТИСТИЧНИЙ АНАЛІЗ ВПЛИВУ АЛГОРИТМІВ СТИСНЕННЯ З ВТРАТАМИ НА СТРУКТУРУ ЦИФРОВИХ ЗОБРАЖЕНЬ

У статті досліджено вплив алгоритмів стиснення з втратами на статистичну структуру цифрових зображень. Стиснення є необхідним етапом зберігання та передавання даних, проте воно змінює первинні характеристики сигналу, що може ускладнювати подальший аналіз у комп'ютерному зорі, дистанційному зондуванні та медичній діагностиці. Традиційні метрики якості (MSE, PSNR, SSIM) не відображають повною мірою статистичних змін, тому актуальним є аналіз гістограм та моментів розподілу цих спотворень. Метою роботи є кількісна оцінка впливу кодеків JPEG, JPEG2000, WebP та AVIF на стохастичні властивості зображень. Для цього було використано два типи даних: синтетичне тестове зображення з чітко визначеною структурою та реальне зображення з природними текстурними неоднорідностями. Обидва зображення стискалися при різних параметрах якості (Q = 30, 50, 70, 90). Подальший аналіз включав побудову гістограм різницевих зображень та обчислення середнього значення, стандартного відхилення, коефіцієнтів асиметрії та ексцесу, а також перевірку просторової узгодженості спотворень. Отримані результати показали, що для досліджуваних кодеків зниження параметру якості Q призводить до зростання дисперсії та ексцесу, при цьому значення середнього та коефіцієнту асиметрії залишаються близькими до нуля. Для синтезованого зображення JPEG2000 спричиняє найбільшу варіацію стохастичних характеристик, а WebP і AVIF – найменшу, причому AVIF генерує дуже вузькі розподіли з високим ексцесом. Водночас для реального стиснутого зображення спостерігається загальне зниження значень стандартного відхилення та ексцесу у порівнянні з синтетичним випадком, а розподіли з «важкими хвостами», характерні для AVIF та WebP на тестових даних, проявляються меншою мірою. Це можна пояснити наявністю природних текстур, на яких похибки компресії розподіляються більш рівномірно. Дослідження просторових залежностей підтвердило локальний характер спотворень без суттєвої кореляції між рядками різницевих зображень. Результати аналізу свідчать, що різні формати по-різному впливають на статистичні властивості зображень. Використання як синтетичних, так і реальних зображень дозволило показати відмінності між граничними сценаріями та практичними умовами застосування досліджуваних кодеків. Результати можуть бути використані для вдосконалення методів оцінювання якості стиснення та розроблення ефективних процедур автоматизованого оброблення та статистичної класифікації зображень.

Ключові слова: *стиснення зображень, JPEG, JPEG2000, WebP, AVIF, статистичний аналіз.*

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Formulation of the problem

Digital image compression is a key stage of modern information and communication processes, in particular in the context of the rapid growth of visual data volumes. Despite the significant advantages associated with reducing the amount of information transmission and storage, compression algorithms inevitably change the original statistical structure of the image. These changes can have a significant impact on further data processing, automated recognition and analysis, which is especially important in such areas as medical diagnostics, remote sensing of the Earth, and computer vision. The relevance of the problem is due to the need to quantify the impact of lossy compression on the preservation of statistical properties of images.

Analysis of recent sources

Analysis of modern scientific studies in the field of digital image processing indicates a significant interest in studying the quality of compression algorithms and their impact on the structure of images. Traditionally, metrics based on direct comparison of the original and compressed image, such as mean square error (MSE), peak signal-to-noise ratio (PSNR) and structural similarity (SSIM), were used for evaluation. These indicators are widely employed in studies [1-3], but their disadvantage is that they do not always correctly or fully reflect the nature of distortions and do not allow assessing the statistical features of the introduced changes. A number of studies [4,5] proposed to take into account histogram characteristics and pixel intensity distribution, but most of the works were focused on the analysis of compressed images themselves, without considering the difference maps between the original and the compressed version. This approach limits the possibilities of a detailed understanding of how each codec changes the statistical structure of the data. Some works [6] are aimed at comparative analysis of the efficiency of modern compression algorithms, but they are mainly focused on subjective visual assessment of artifacts or on the use of traditional quality indicators. At the same time, the authors use real remote sensing data, which contain heterogeneous and uncontrolled characteristics, which complicates the quantitative assessment of the impact of compression factors on specific classes of objects. In [7], the results of a statistical analysis of distortions caused by image compression using the BPG codec are presented. To account for the impact of noise on image quality after decompression, white Gaussian noise (AWGN) was added to the original images. It is shown that for the original images, the distortions introduced by lossy compression have a predominantly non-Gaussian distribution, whereas in the presence of AWGN, a tendency toward a normalization of the distortion distribution is observed.

The aim of the work is: to conduct a systematic analysis of the impact of different compression algorithms (JPEG, JPEG2000, WebP, AVIF) on the stochastic properties of images. The study involves constructing histograms of difference images and calculating the mean, standard deviation, skewness and kurtosis for different values of the quality parameter Q. The results of the analysis allow identifying specific changes caused by each algorithm and to assess the degree of preservation or change of the original statistical parameters.

Presenting main material

The study used common lossy codecs: from traditional JPEG and JPEG2000 [8, 9] to modern WebP and AVIF [9, 10]. JPEG is considered one of the most versatile and compatible codecs. It is based on a discrete cosine transform in 8×8 pixel blocks, which can lead to blocky artifacts in compressed images. JPEG2000 uses a discrete wavelet transform for compression, which allows for higher image quality with the same compression ratio. It also provides better preservation of details, highlights, and edges in images. WebP is a modern hybrid codec based on the VP8 video compression method. In most cases, it offers a better size-to-quality ratio than JPEG. Compression is achieved by reducing the quality of fine details and textures. Smooth changes in brightness and edges are preserved in homogeneous areas of the image. AVIF compression is based on the AV1 video codec, a more modern version of VP8. Therefore, the AVIF format can maintain slightly higher image quality than WebP while significantly reducing file size [11]. Thus, using these codecs, it is possible to evaluate the impact of lossy compression on the spatial structure of images and to investigate the stochastic properties of distortions introduced into the original images.

A test image with an artificially created brightness structure, shown in Fig. 1 [1], was chosen for the analysis. The use of such a synthetic image is justified by its ability to provide controlled conditions for observing the influence of distortions. In addition, a real 512×512-pixel image obtained using three Sentinel-2 optical spectral channels and depicting the Kharkiv region (Fig. 2), also used in [1], was analyzed.

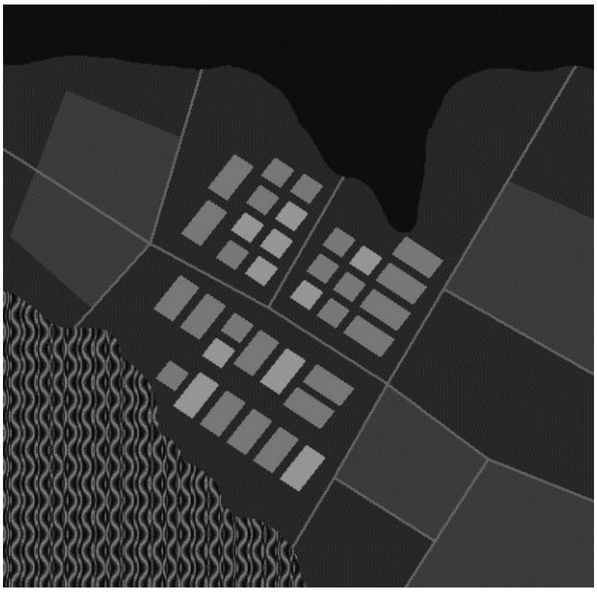


Fig. 1. Image with artificial brightness structure (ImA)

Fig. 2. Real satellite image (ImR)

It was expected that complex textures and color variations in natural images would obscure the effects of compression, while the synthetic image would provide more accurate detection and quantification of lossy compression artifacts. Therefore, such a structured template could serve as a reference object, facilitating the systematic evaluation of codec performance under various quality settings. Unlike the artificially generated structure, this natural scene enables verification of the codecs' behavior under more realistic conditions. The image has a relatively simple structure, allowing identification of four generalized object classes – constructions (buildings, roads, dam), reservoir, vegetation, and bare soil, each represented by statistically homogeneous regions in RGB brightness. This makes it suitable for assessing how compression artifacts manifest not only in controlled but also in practical Earth observation tasks.

Test images were compressed using chosen codecs. For each codec, four quality parameter (Q) values were used: 30, 50, 70, and 90. This quality parameter value is a general measure of compression: lower values, such as 30, correspond to stronger compression with more pronounced distortion, while higher values (such as 90) preserve most of the original content with minimal loss. However, despite identical quality parameter values, algorithm implementation details may result in differences in the nature of compression artifacts.

For statistical analysis of the distortions introduced by the compression of the original images, so-called difference images were formed as the results of element-by-element subtraction of the pixel values of the compressed image from the corresponding values of the original test image of the same dimension:

$$D(x,y) = I_{orig}(x,y) - I_{comp}(x,y)\,, \tag{1}$$

where $I_{orig}(x,y)$ is the intensity of the original image pixel, $I_{comp}(x,y)$ is the intensity after compression.

Figs 3–6 show distortion histograms obtained for the JPEG, JPEG2000, WebP, and AVIF codecs at given Q levels, which represent the distributions of pixel intensity variations for different compression levels.

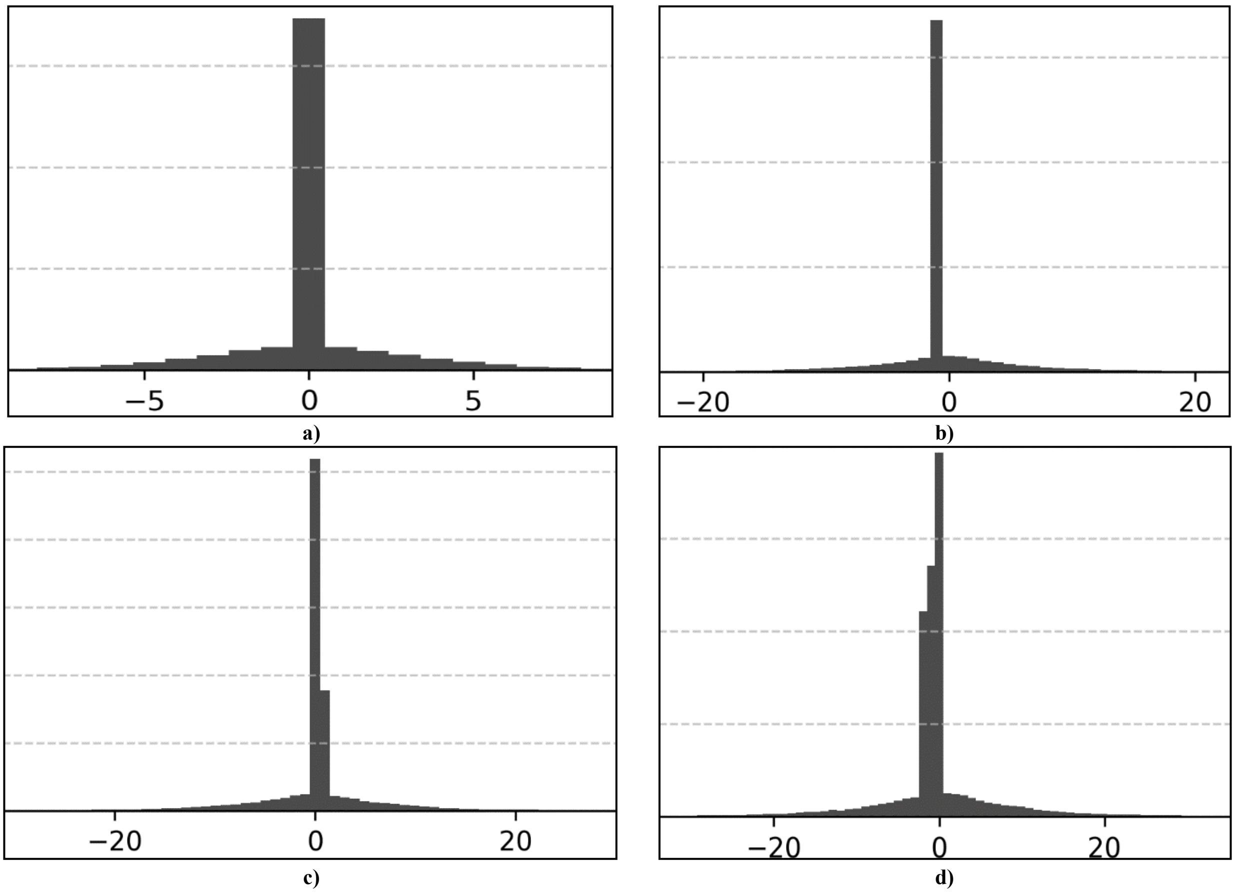


Fig. 3. JPEG codec distortion histograms for the image ImA: a) Q = 90; b) Q = 70; c) Q = 50; d) Q = 30

The following numerical stochastic characteristics were also calculated: mean, variance, skewness, and kurtosis. These parameters allow us to identify changes in the intensity distribution due to the specifics of each compression algorithm and the selected quality level. The mean characterizes the systematic error of the introduced distortions, while the variance characterizes the random error. Skewness and kurtosis are quantitative measures of the shape of a distribution and are often used to test the hypothesis that the empirical distribution is normal, for which the values of these indicators are zero.

Tables 1–4 present the corresponding statistical parameters for each codec.

Table 1

Statistical characteristics of JPEG codec distortions for the image ImA

Q	Mean	Std	Skewness	Kurtosis
90	0.0	2.28	-0.0	5.85
70	-0.65	4.77	0.36	8.76
50	0.16	5.74	-0.04	9.51
30	-0.49	6.90	0.19	8.78

For the classical JPEG codec, a reduction of the quality parameter (Q) is consistently associated with an increase in the standard deviation (Std) of distortions (i.e., pixel differences): from 2.28 at Q = 90 to 8.02 at Q = 20. This trend is explained by the intensified quantization of high-frequency coefficients at lower quality levels. The mean value remains close to zero, which confirms the practical absence of a systematic bias, although local fluctuations within ±1.2 are observed. The skewness coefficient is small and alternates in sign, reflecting a relative balance between positive and negative distortions. By contrast, the kurtosis coefficient demonstrates growth as Q decreases, reaching 9.51 at Q = 50, which indicates the emergence of heavier distribution tails and a higher frequency of extreme values.

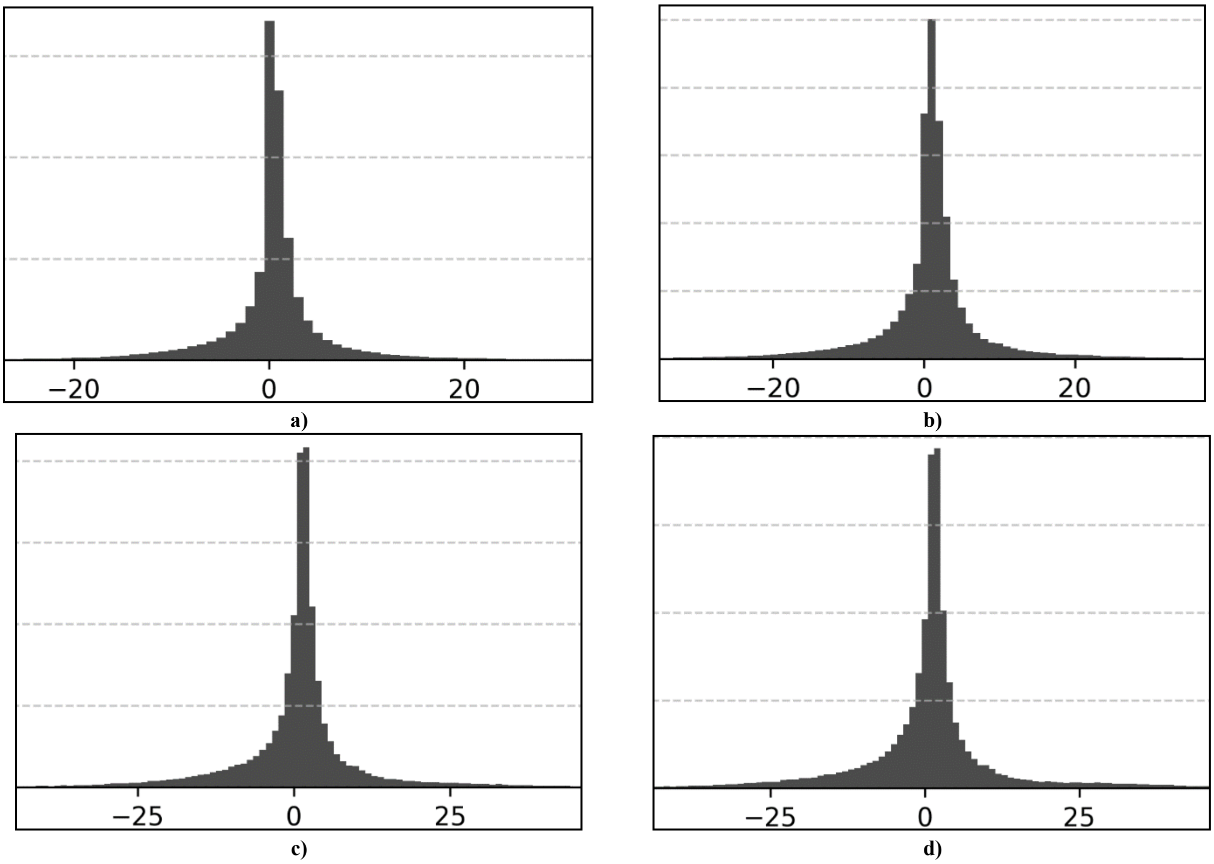


Fig. 4. JPEG2000 codec distortion histograms for the image ImA: a) Q = 90; b) Q = 70; c) Q = 50; d) Q = 30

Table 2

Statistical characteristics of JPEG2000 codec distortions for the image ImA

Q	Mean	Std	Skewness	Kurtosis
90	0.26	5.74	-0.23	8.0
70	0.73	7.59	-0.21	7.79
50	0.69	9.96	0.01	7.10
30	0.59	11.65	0.17	5.74

A comparative analysis of statistical characteristics reveals substantial differences between the JPEG2000 and JPEG codecs under equivalent quality parameter (Q) levels. In particular, JPEG2000 exhibits higher values of standard deviation compared to JPEG. For example, at Q=50, the standard deviation for JPEG2000 reaches 9.96, whereas for JPEG it is only 5.74. This discrepancy suggests that data reconstructed using JPEG2000 is characterized by greater variability. The mean values remain slightly positive, indicating a minor systematic tendency toward positive deviations. However, this bias is not substantial. The analysis of skewness further demonstrates that its values are generally close to zero, implying that the distributions are predominantly symmetric. With decreasing Q, kurtosis values gradually decline from 8.0 to 5.74. This trend may be interpreted as an indication of histogram broadening, which in turn reflects a reduction of the distribution's peak height and a more uniform dissipation of values.

The analysis of the WebP codec for the synthesized image shows lower standard deviation values compared to JPEG and JPEG2000. Thus, compression by the WebP codec leads to a reduction in the variability of distortions in the images. Skewness is steadily positive (~0.4–0.5), suggesting a slight dominance of positive deviations. Kurtosis increases monotonically from 6.86 to 10.44, which reflects the formation of increasingly sharp histogram peaks with heavy tails. Thus, WebP compression produces error distributions that are both more concentrated around the mean and more prone to extreme values, distinguishing it from the broader, flatter distributions observed in JPEG2000.

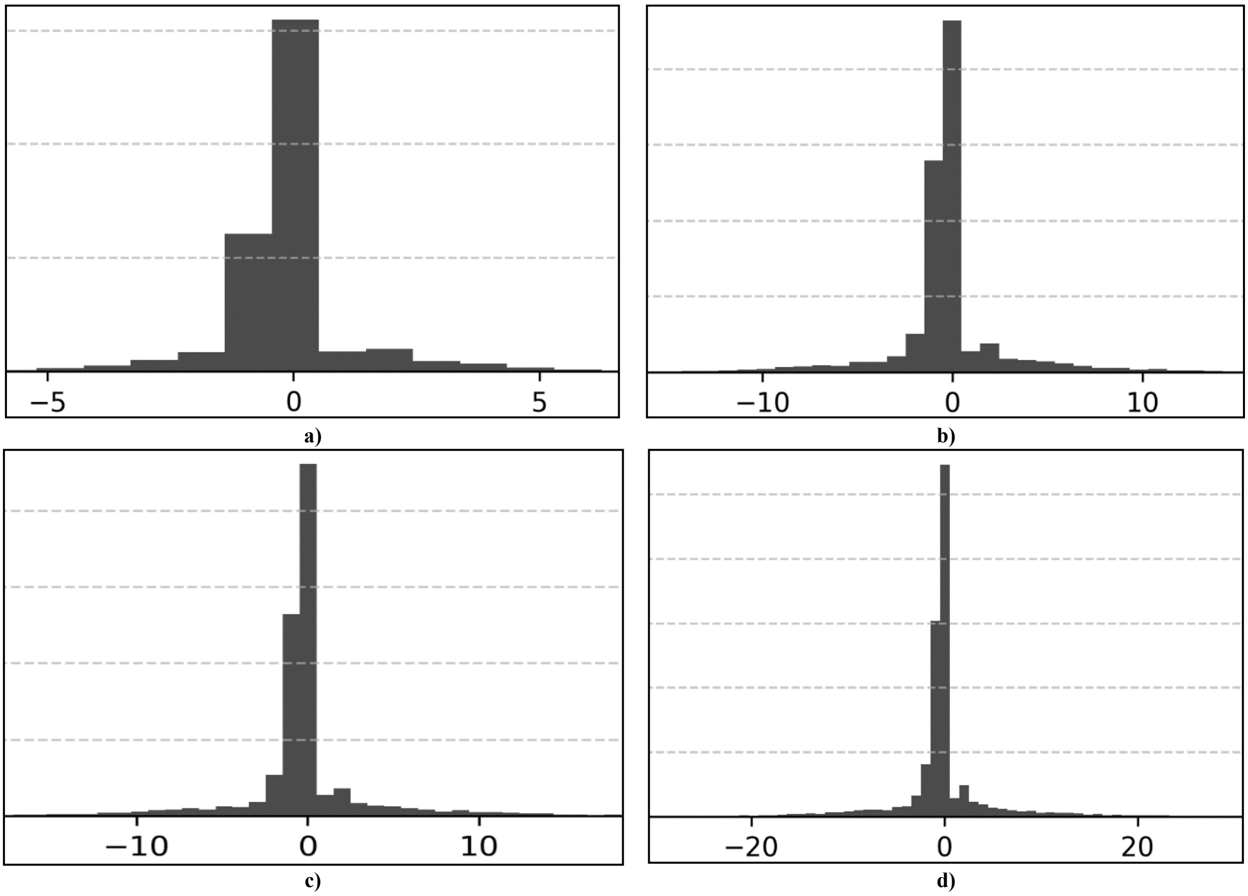


Fig. 5. WebP codec distortion histograms for the image ImA: a) Q = 90; b) Q = 70; c) Q = 50; d) Q = 30

Table 3

Statistical characteristics of WebP codec distortions for the image ImA

Q	Mean	Std	Skewness	Kurtosis
90	-0.17	1.33	0.47	6.86
70	-0.24	3.20	0.39	8.83
50	-0.23	3.98	0.41	9.25
30	-0.25	5.26	0.47	10.44

AVIF shows the lowest deviation values among all other codecs for the synthesized image ImA. The standard deviation reaches only 0.5 at Q=90 and 4.79 at Q=30. This result indicates high compression efficiency while preserving image quality. The kurtosis reaches extremely high values (up to 32.56 at Q=70), which indicates narrow histograms with an extremely pronounced peak. The asymmetry varies, but remains moderate, not exceeding 0.65.

To assess the spatial structure of the changes introduced into the image as a result of the codec application, normalized correlation coefficients between rows of the difference image were calculated. In the first stage, each row of the difference image was normalized: the mean value was subtracted from it, after which the result was divided by the standard deviation. This allowed us to exclude the influence of amplitude characteristics and focus on the mutual nature of brightness changes. Rows with a standard deviation close to zero were not included in the calculation. After that, Pearson correlation coefficients were calculated between the first row and each subsequent row by formula:

$$p_{ij} = \frac{\sum_k \left(X_{i,k} - \bar{X}_i\right)\left(X_{j,k} - \bar{X}_j\right)}{\sqrt{\sum_k \left(X_{i,k} - \bar{X}_i\right)^2 \sum_k \left(X_{j,k} - \bar{X}_j\right)^2}}, \quad (2)$$

where $X_{i,k}$ is the distortion at column k in row i.

Table 4

Statistical characteristics of AVIF codec distortions for the image ImA

Q	Mean	Std	Skewness	Kurtosis
90	-0.01	0.50	-0.34	16.76
70	0.02	1.13	-0.01	32.56
50	-0.02	2.84	0.65	30.43
30	-0.02	4.79	0.4	19.59

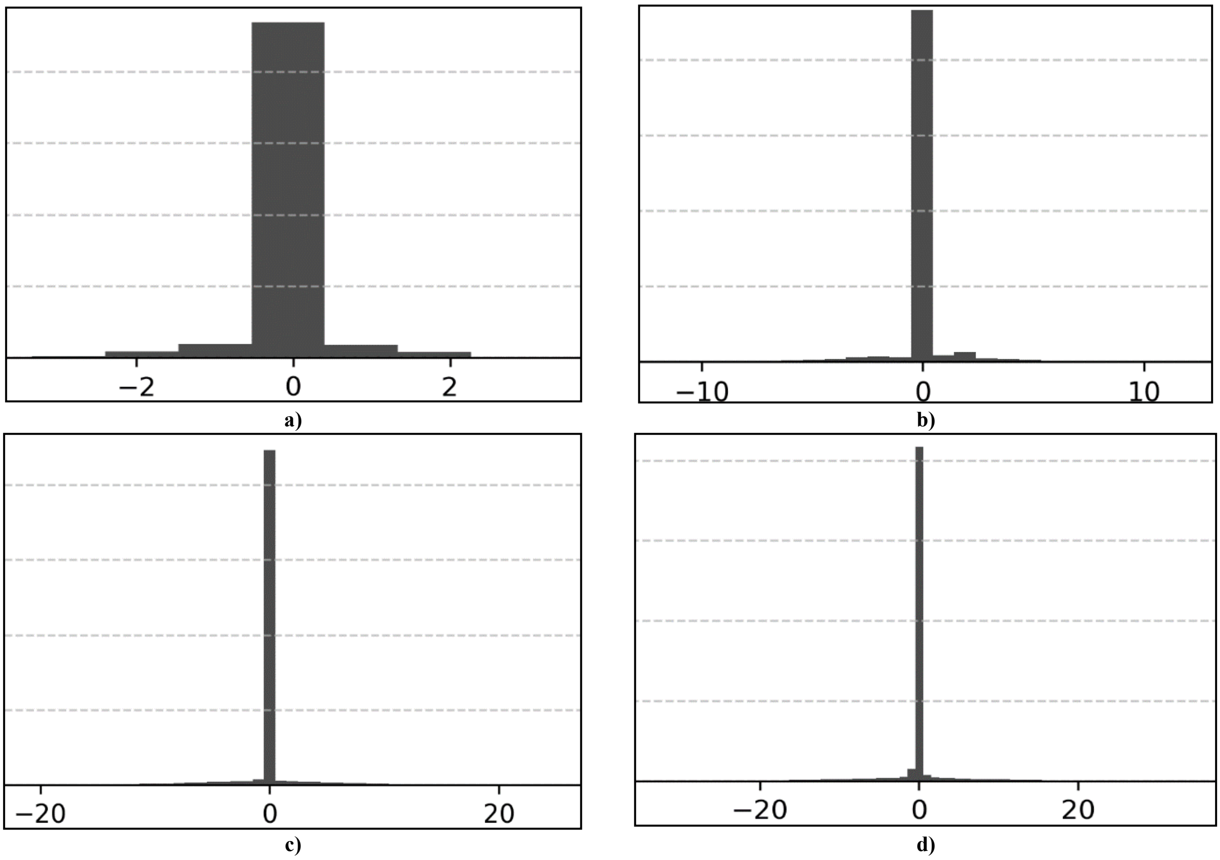


Fig. 6. AVIF codec distortion histograms for the image ImA: a) Q = 90; b) Q = 70; c) Q = 50; d) Q = 30

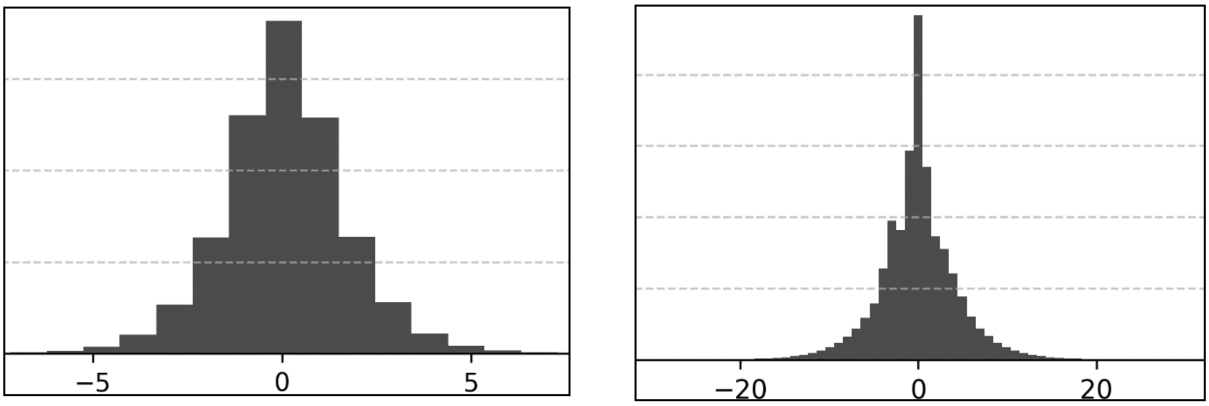
The process continued until the value of the coefficient remained greater than 0.1 in modulus. This approach allows determining the vertical consistency limit, that is, the number of rows in which the nature of changes is similar to the first. Based on the obtained number of rows, a square correlation matrix was formed, reflecting the degree of similarity between all pairs of these rows. In the process of analyzing the normalized correlation coefficients between the rows of the difference image, it was found that for most images the correlation interval does not exceed five rows. Moreover, strong ($|p_{ij}| > 0.7$) or noticeable ($|p_{ij}| = 0.5…0.7$) correlations were observed only between two adjacent rows. As an example, Table 5 shows the correlation matrices for JPEG2000 codec distortions at Q=90 and Q=50.

Table 5

Correlation matrices of the JPEG2000 codec distortions for rows with indices 60–65 of the ImA image

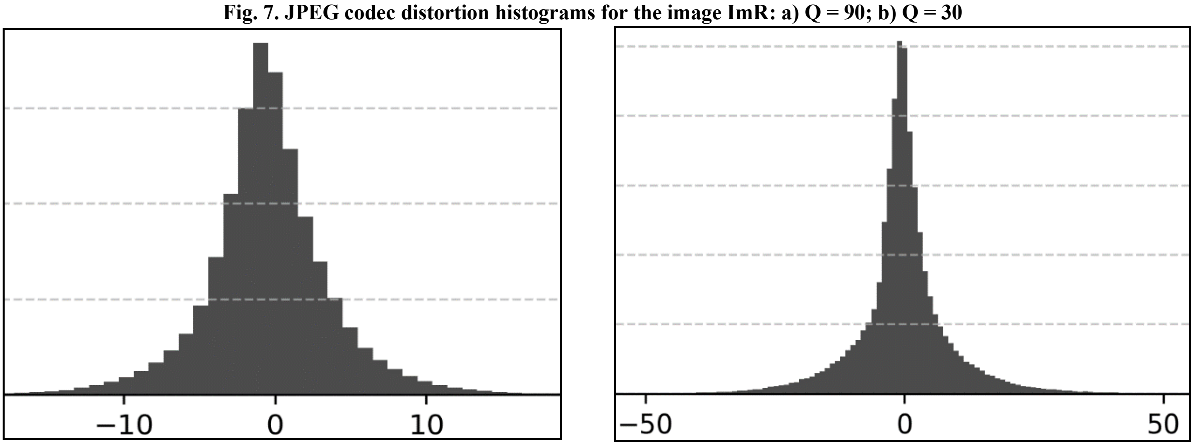
Q=90							Q=50					
1	0.359	0.256	0.136	-0.084	0.029		1	0.704	0.488	0.258	-0.044	-0.037
0.359	1	0.386	0.177	0.082	-0.098		0.704	1	0.676	0.424	0.048	-0.166
0.256	0.386	1	0.483	0.315	0.262		0.488	0.676	1	0.707	0.235	0.047
0.136	0.177	0.483	1	0.375	0.182		0.258	0.424	0.707	1	0.554	0.271
-0.084	0.082	0.315	0.375	1	0.271		-0.044	0.048	0.235	0.554	1	0.672
0.029	-0.098	0.262	0.182	0.271	1		-0.037	-0.166	0.047	0.271	0.672	1

The results obtained for the synthetic image allow identifying the limiting properties of compression algorithms and analyze the characteristic patterns of statistical changes under controlled conditions. However, the synthetic test image does not fully reflect the complexity of natural scenes, where there are textural heterogeneities, noise components and local contrast transitions. These factors can significantly affect the distribution of errors after compression and modify the overall statistical picture. In order to assess the practical relevance of the results obtained, the next stage of the study was the analysis of a real image, which allows tracing how the described trends manifest themselves in the conditions of the natural signal structure. For the study, the image was first converted to grayscale and then subjected to compression using the same codecs (JPEG, JPEG2000, WebP, AVIF) and quality parameters (Q = 30, 50, 70, 90) as in the synthetic case. This ensured comparability of the obtained statistical characteristics across both experimental setups. The corresponding histograms and tables of statistical metrics are presented in Tables 6-9 and Figs. 7-10). The distortion histograms are shown for two extreme values of the quality parameter: Q=90 and Q=30.



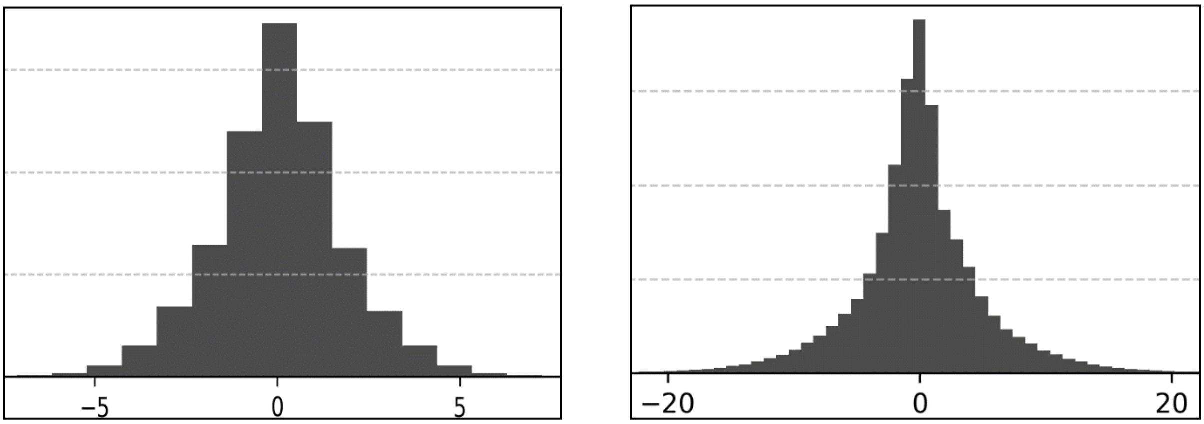
a) b)

Fig. 7. JPEG codec distortion histograms for the image ImR: a) Q = 90; b) Q = 30



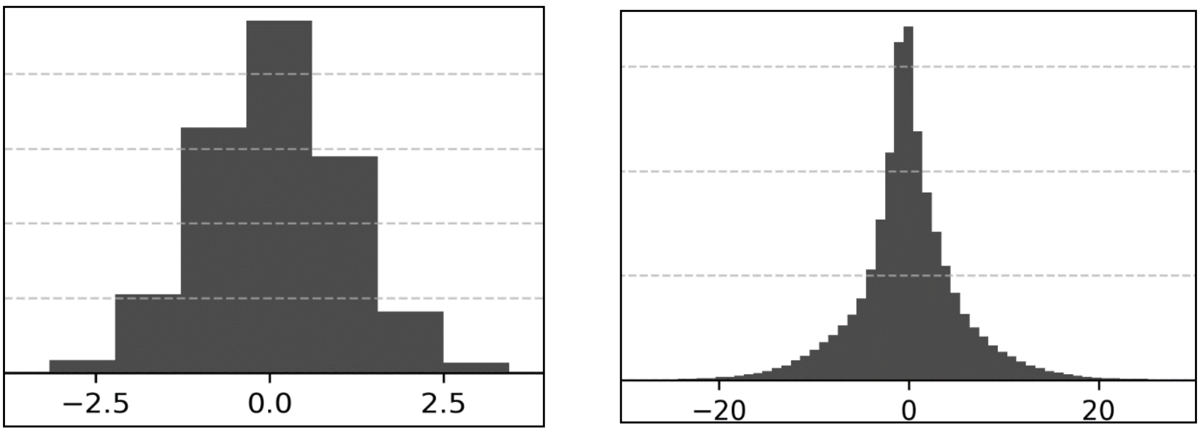
a) b)

Fig. 8. JPEG2000 codec distortion histograms for the image ImR: a) Q = 90; b) Q = 30



a) b)

Fig. 9. WebP codec distortion histograms for the image ImR: a) Q = 90; b) Q = 30



a) b)

Fig. 10. AVIF codec distortion histograms for the image ImR: a) Q = 90; b) Q = 30

Table 6

Statistical characteristics of JPEG codec distortions for the image ImR

Q	Mean	Std	Skewness	Kurtosis
90	0.02	1.74	0.07	1.5
70	0.0	2.86	0.1	3.31
50	0.0	3.58	0.05	3.7
30	-0.03	4.53	0.1	4.0

Table 7

Statistical characteristics of JPEG2000 codec distortions for the image ImR

Q	Mean	Std	Skewness	Kurtosis
90	-0.49	4.31	0.1	3.47
70	-0.66	5.57	0.12	4.14
50	-0.33	7.85	0.11	4.86
30	-0.41	9.46	0.19	5.77

Table 8

Statistical characteristics of WebP codec distortions for the image ImR

Q	Mean	Std	Skewness	Kurtosis
90	-0.01	1.86	0.0	0.76
70	-0.02	3.52	0.02	1.92
50	-0.03	4.23	0.02	2.37
30	-0.06	5.33	0.03	3.39

Table 9

Statistical characteristics of AVIF codec distortions for the image ImR

Q	Mean	Std	Skewness	Kurtosis
90	-0.07	1.14	0.1	0.59
70	-0.08	2.22	0.06	0.84
50	-0.1	3.54	0.12	2.23
30	-0.07	5.8	0.09	3.51

Analysis of the results obtained on a real image revealed significant differences from the experiments with the synthetic test. For JPEG, a lower level of standard deviation (1.74-4.53) and significantly smaller values of kurtosis (1.50-4.00) are observed, which is explained by the smoothing effect of natural texture complexity, which reduces the severity of quantization errors. In the case of JPEG2000, the standard deviation remains lower compared to the synthetic data (4.31-9.46), while the kurtosis acquires moderate values (3.47-5.77), which indicates a more uniform distribution of errors in complex texture areas. For WebP, the standard deviation level is preserved, similar to the synthetic case (1.86-5.33), but the kurtosis is reduced by almost three times (0.76-3.39), which indicates the absence of sharply pronounced peaks in the distributions. The most pronounced differences are recorded for AVIF: despite maintaining a low standard deviation (1.14-5.80), the kurtosis remains tens of times smaller (0.59-3.51) than in the synthetic image, which is explained by the influence of natural textures that prevent the formation of over-peak histograms. The totality of these results confirms that real data is characterized by more “soft” statistical changes, which reflects the specifics of the interaction of compression algorithms with the natural textural features of the image.

Table 10 presents examples of correlation matrices of the JPEG2000 codec distortions for six rows of the ImR image. An analysis of the normalized correlation coefficients between rows of the real difference image revealed a pattern similar to the synthetic case: significant correlations are observed primarily for two to four adjacent rows. This result can be explained by the local nature of the distortions. In real images, the presence of heterogeneous textures and irregular structural details prevents the formation of vertically consistent artifacts, thereby eliminating systematic inter-row dependencies and confirming the conclusion about the predominant spatial localization of the distortions.

Table 10

Correlation matrices of the JPEG2000 codec distortions for rows with indices 10–15 of the ImR image

Q=90							Q=50					
1	0.653	0.42	0.131	0.019	0.073		1	0.749	0.398	-0.012	-0.139	-0.031
0.653	1	0.58	0.123	0.043	0.004		0.749	1	0.717	0.184	-0.064	-0.041
0.42	0.58	1	0.487	0.264	0.139		0.398	0.717	1	0.62	0.368	0.188
0.131	0.123	0.487	1	0.509	0.071		-0.012	0.184	0.62	1	0.828	0.393
0.019	0.043	0.264	0.509	1	0.513		-0.139	-0.064	0.368	0.828	1	0.692
0.073	0.004	0.139	0.071	0.513	1		-0.031	-0.041	0.188	0.393	0.692	1

Conclusions

The study demonstrated that lossy compression algorithms affect image statistics differently depending on the codec and the type of input data. On synthetic images, JPEG and WebP caused strong increases in kurtosis and skewness, while JPEG2000 preserved more natural distributions and AVIF produced extremely peaky histograms despite low variance. In contrast, real images exhibited considerably milder distortions: both standard deviation and kurtosis remained lower, and extreme peakiness was not observed. This difference is attributed to the heterogeneous textures of real scenes, which distribute compression artifacts more evenly and reduce statistical extremities. For both synthetic and real data, spatial analysis confirmed the local nature of distortions and the absence of vertical coherence, making correlation matrices formally possible but practically uninformative.

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