Information systems research

UDC 528.852.1:004.932 **doi:** https://doi.org/10.20998/2522-9052.2024.3.04

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POST-FILTERING OF LOSSY COMPRESSED NOISY IMAGES AND ITS EFFICIENCY PREDICTION

Abstract. The object of the study is the process of lossy compression of noisy images and their post-filtering. **The subject of the study** is the approach to efficient two-stage processing (compression and post-filtering) for better portable graphics (BPG) coder and prediction of its efficiency. **The goal of the study** is to analyze performance characteristics of the considered two-stage approach and to propose an approach to their prediction. **Methods used:** numerical simulation, regression, statistical analysis. **Results obtained:** 1) the considered approach advantage is that it is able to provide improvement of quality of compressed noisy image under condition that an image is compressed with compression ratio smaller than that one corresponding to optimal operation point; 2) the approach efficiency depends on several factors including noise intensity, image complexity, and filter type and parameters; 3) the main characteristics of the two-step procedure can be quite accurately predicted in advance and this allows offering useful information for decision undertaking on what value of the coder parameter to apply; 4) this leads to either improving the compressed and processed image quality compared to its original version or, at least, to avoiding quality degradation. **Conclusions:** based on the results of the study, it is worth 1) predicting performance characteristics for the two-stage processing; 2) adapting the processing to image complexity and noise intensity.

Keywords: lossy image compression; quality control; noise; two-step processing; prediction.

Introduction

A tremendous number of images of different origin is acquired nowadays by different imaging systems [1–3]. This takes place in medical diagnostics [1], remote sensing [2], military reconnaissance [3], social networking [4], and so on. In addition, average image size becomes larger due to improved spatial resolution and the use of more components of multispectral [5] and hyperspectral [6] data. This results in problems dealing with image storage and transfer via communication lines [7]. Compression is known as a tool to decrease the data size [5–7] where lossless image compression [7, 8] is reversible but often unable to provide appropriately large and variable compression ratio (CR). Because of this, lossy compression is widely used [5, 6, 8]. Such a compression introduces distortions [5, 9] and, then, it occurs necessary to provide an appropriate trade-off between a compressed image quality according to a used metric and CR [9, 10].

Reaching the trade-off is carried out in two ways. First, a coder able to provide the best (or nearly the best) rate/distortion curves (for a set of images) is chosen. In this sense, the better portable graphics (BPG) encoder [11–13] can be considered as one of the best. This was one of the reasons to concentrate on considering this encoder in our studies. Second, it is usually assumed that distortions increase if CR becomes larger [9, 10, 14]. In other words, a rate/distortion curve (RDC) that characterizes dependence of a metric that describes distortions on a parameter that controls compression (PCC) occurs to be monotonous.

This simplifies the task of reaching the aforementioned trade-off and allows using either iterative procedures [14] or a two-step approach [13] or an approach based on prediction [15].

All this is true if one deals with lossy compression of noise-free images. However, a lot of images that are acquired by different systems and have to be compressed are noisy [6, 16, 17]. This relates to optical images acquired in bad illumination conditions, medical and radar images. For such images, lossy compression has two specific effects [6, 17]. The first effect is the existence of a specific noise filtering effect due to lossy compression discovered at the end of the previous century [17, 18]. The second effect is possible existence of the so-called optimal operation point (OOP), e.g. such a value of PCC that a compressed image is maximally close to the corresponding noise-free (true) image according to a given similarity (quality) metric. Note that both standard metrics (such as mean square error or peak signal-to-noise ratio) and visual quality metrics [19–21] can be used [6, 22].

If OOP exists, then it is reasonable to compress an image at hand in OOP neighborhood [6, 17, 22]. This allows producing the compressed image of rather high quality and quite large CR. In turn, if OOP does not exist for an image subject to lossy compression, it is expedient to compress it with a smaller CR since this introduces less distortions into information content. Note that since one does not have noise-free images in practice, it is impossible to determine does OOP exist or not for a given noisy image and what is OOP very accurately. Fortunately, for some coders including the BPG one, quite simple procedures for prediction of OOP existence and CCP in OOP have been designed for the cases of additive white Gaussian noise (AWGN) and signal-dependent Poisson noise [6, 22].

Moreover, it has been shown recently [23] that quality of compressed noisy images can be additionally improved by their post-filtering after decompression. Both a DCT-based [24] and block-matching

3-dimensional (BM3D) [25] filters have been shown useful where the latter is slightly more efficient under condition that thresholds are properly set for both filters. Note that thresholds for both filters are usually set as T=βσ where σ is the noise standard deviation and β is the adjustable proportionality factor. If Q for the BPG encoder increases and σ for the original noisy image is known a priori or accurately pre-estimated, the optimal β decreases since intensity of the noise in compressed images is lower than in original ones and to avoid over-smoothing.

The problems with the two-stage approach [23] that presumes post-filtering of lossy compressed noisy images are the following. First, it has been tested for only two images that are remote sensing ones, i.e. of specific class. Second, possibilities of prediction of the efficiency of this two-stage approach have not been studied.

Thus, the **object of our study** is the process of two-stage processing of noisy images that includes their lossy compression by the BPG encoder and further denoising by the BM3D filter. Our **basic idea** is the following. OOP existence can be predicted in advance [22]. Denoising efficiency can be predicted in advance as well [26]. Then, it seems possible to predict the performance of the two-stage processing procedure in general.

The goals of this paper is to check this idea and to give practical recommendations on its use in practice.

Background of the two-stage approach

For simplicity and without losing generality (an appropriate variance stabilizing transform can be applied before compression if noise is signal-dependent under condition that its statistical characteristics are a priori known), consider the case of AWGN having zero mean and a priori known variance σ^2. Then, for conventional 8-bit representation of input data, for a considered grayscale image one has input peak signal-to-noise ratio (PSNR) defined as

$$PSNR_{inp} = 10\log_{10}(255^2/\sigma^2). \quad (1)$$

Let us denote PSNRs of lossy compressed image $\mathbf{I_c}$ and post-filtered image $\mathbf{I_p}$ as $PSNR_{ct}$ and $PSNR_{pft}$ where

$$SNR_{ct}=10\log_{10}(255^2/MSE_{ct}), \quad (2)$$

$$PSNR_{pft}=10\log_{10}(255^2/MSE_{pft}), \quad (3)$$

where MSE_{ct} and MSE_{pft} are mean square errors calculated for compressed and post-filtered images with respect to the corresponding noise-free (true) image $\mathbf{I_t}$ supposed known in our experiments.

Consider now difference PSNRs determined as

$$PSNR_{p1}=PSNR_{ct}-PSNR_{inp}, \quad (4)$$

$$PSNR_{p2}=PSNR_{pft}-PSNR_{inp}. \quad (5)$$

as functions of CR. Here, we present examples for the BPG encoder and BM3D filter with optimal β from the paper [23] for two test images: FR01 (that contains a lot of small-sized details and textures) and Frisco (that has quite simple structure and has a lot of pixels belonging to image homogeneous regions). In both cases, noise variance (Var) is equal to 50.

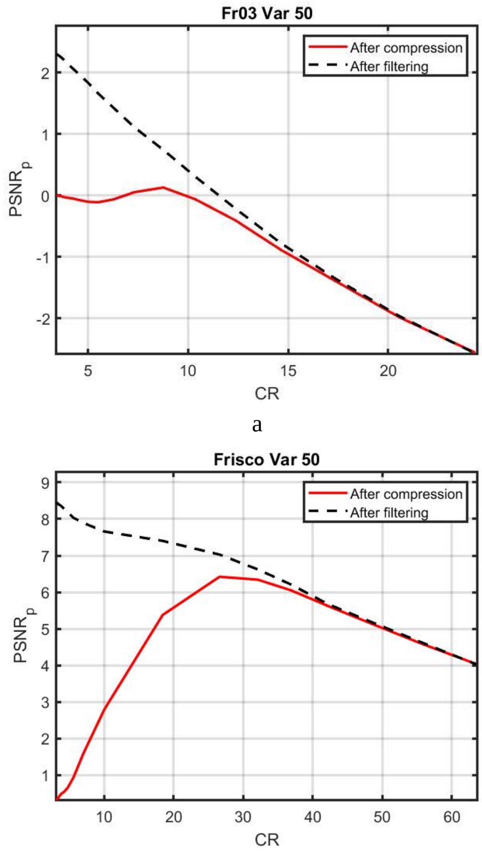


Fig. 1. Dependences of $PSNR_{p1}$ (after compression) and $PSNR_{p2}$ (after filtering) on CR for Fr01 (a) and Frisco (b) test images corrupted by AWGN with noise variance equal to 50

Analysis of the curves in Fig. 1, a shows the following. First, formally OOP exists for $CR_{OOP} \approx 8$ but it is not "obvious". For smaller CR, post-filtering provides certain benefits in image quality ($PSNR_{p2} \approx 2$ dB for CR≈5). However, for $CR > CR_{OOP}$, post-filtering becomes practically useless and, for CR > 12, both $PSNR_{p1}$ and $PSNR_{p2}$ become negative. Analysis of the plots in Fig. 1, b shows that OOP takes place for $CR_{OOP} \approx 26$ and it is "obvious", i.e. $PSNR_{p1}$ is large. Again, post-filtering is beneficial for $CR < CR_{OOP}$ and $PSNR_{p2}$ reaches ≈ 8 dB. On the opposite, for $CR > CR_{OOP}$, post-filtering is practically useless although $PSNR_{p1}$ and $PSNR_{p2}$ remain positive for a wide range of CR variation. CR_{OOP} for simple structure images is significantly larger than for more complex image for the same noise variance.

Summarizing the presented conclusions as well as the results presented in [23], it is possible to state the following. First, post-filtering can be efficient, especially for simple structure images and/or intensive noise, but only under condition that $CR < CR_{OOP}$ (or, equivalently, $Q < Q_{OOP}$ where Q serves as PCC for the BPG encoder, a larger Q correspond to a larger CR). Second, for $CR > CR_{OOP}$ ($Q > Q_{OOP}$), post-filtering becomes useless. For complex structure images, compression with $Q > Q_{OOP}$ cannot be recommended at all (moreover, it is possible to recommend compression with Q slightly smaller than Q_{OOP}). For simple structure images, it seems possible to compress images with Q slightly larger than Q_{OOP} (without post-processing, if a larger CR is strongly desired), but it is unclear what can be the largest appropriate $Q - Q_{OOP}$.

Before coming to analysis of new data, it is worth recalling that Q_{OOP} can be easily determined as $Q_{OOP} = 15 + 20\log_{10}(\sigma)$ whilst optimal $\beta \approx 2.6$ for $Q < Q_{OOP}$-3 and $\beta \approx 2.0$ for $Q \approx Q_{OOP}$ [23]. Existence of OOP is more likely for more intensive noise. Thus, we need more test data obtained as functions of Q for wider limits of noise variance.

Analysis of the results obtained for new test data

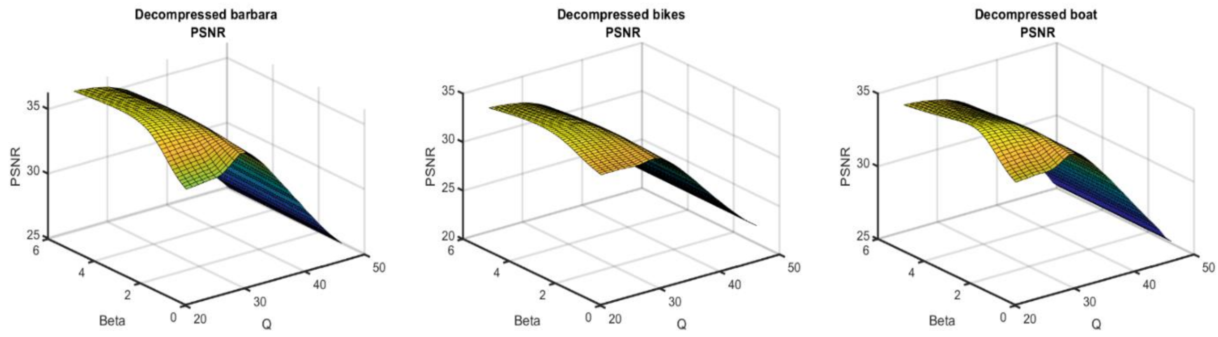
We have carried out analysis for three optical grayscale images, namely Barbara, Bikes, and Boat (all of middle complexity). Three values of noise variance have been considered: 50, 100, and 200. In addition to the metric PSNR, the visual quality metrics PSNR-HVS-M [24, 25] and FSIM [27] have been employed. Both have larger values for images of better visual quality. PSNR-HVS-M is expressed in dB, FSIM varies in the limits from 0 to 1 where unity corresponds to perfect quality.

Fig. 2 shows the dependences of $PSNR_{pft}$ on Q and β for $\sigma^2 = 50$ ($P_{inp} = 31.2$ dB) for all three images. The case of minimal considered β can be treated as dependence of $PSNR_{ct}$ on Q. As one can see, OOP is present for all three test images where it is the most obvious for the test image Barbara. Optimal β is about 2.8 for $Q < 30$ ($Q_{OOP} = 32$), but it is smaller for $Q \approx Q_{OOP}$. This means that the main conclusions are the same as for remote sensing images earlier studied in [23]. Dependences of PSNR-HVS-M_{pft} on Q and β for $\sigma^2 = 50$ (input PSNR-HVS-M is not the same and it is 38 dB for the image Barbara, 37.5 dB for the image Bikes, and 37 dB for the image Boat) for all three images are represented in Fig. 3. According to this metric, OOPs are not observed but post-processing slightly improves visual quality for Q smaller than Q_{OOP}. Increasing of Q for $Q > Q_{OOP}$ leads to radical reduction of processed image quality.

Dependences $PSNR_{pft}$ on Q and β for $\sigma^2 = 200$ ($P_{inp} = 25.2$ dB, $Q_{OOP} \approx 38$) are given in Fig. 4. For all three test images, OOPs are observed and compression in OOP provides considerable benefits compared to compression with $Q < Q_{OOP} - 4$ and $Q > Q_{OOP} + 4$. In other words, significant improvement of compressed image quality is observed not for all Q, but only for a limited area of $Q_{OOP} - 4 < Q < Q_{OOP} + 4$. In turn, for $Q < Q_{OOP} - 4$, there is a significant improvement due to compressed image post-filtering with $\beta \approx 2.6$.

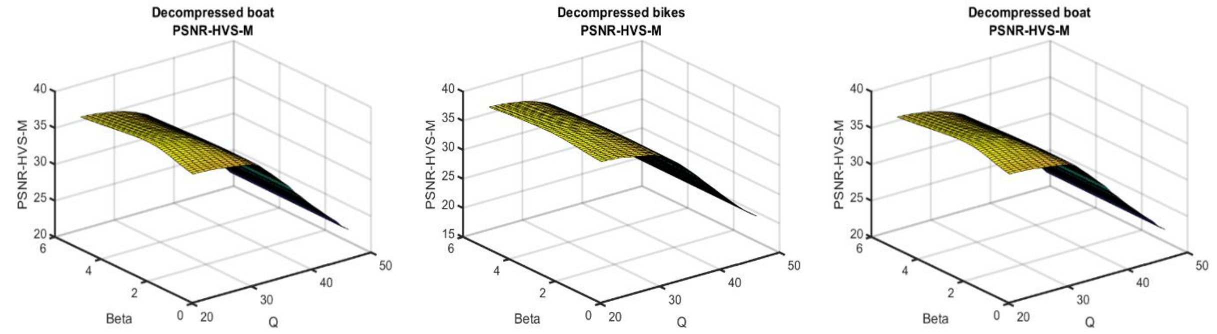
Fig. 5 presents dependences of PSNR-HVS-M_{pft} on Q and β for $\sigma^2 = 200$. Only for the image Barbara, the lossy compression in OOP produces improvement of visual quality. Meanwhile, post-filtering improves it for $Q < Q_{OOP} - 4$. The results for the metric PSNR-HVS-M are in good agreement with the results for the other visual quality metric FSIM (see data in Fig. 6).

In addition to data presented in Fig. 2–6, we have collected data in Table 1. The following data are presented: $\delta PSNR = PSNR_f - PSNR_{inp}$ where $PSNR_f$ is the output PSNR for BM3D applied directly to the noisy image (without lossy compression); $\delta PSNR_{pred}$ denotes the predicted δPSNR (details will be given later); $PSNR_{p2}(Q_{OOP}$-5); $PSNR_{p2}(Q_{OOP})$; $PSNR_{ct\ pred}$ that denotes predicted improvement in PSNR due to lossy compression in OOP, see details below; $PSNR_{p2}(Q_{OOP}$+5).



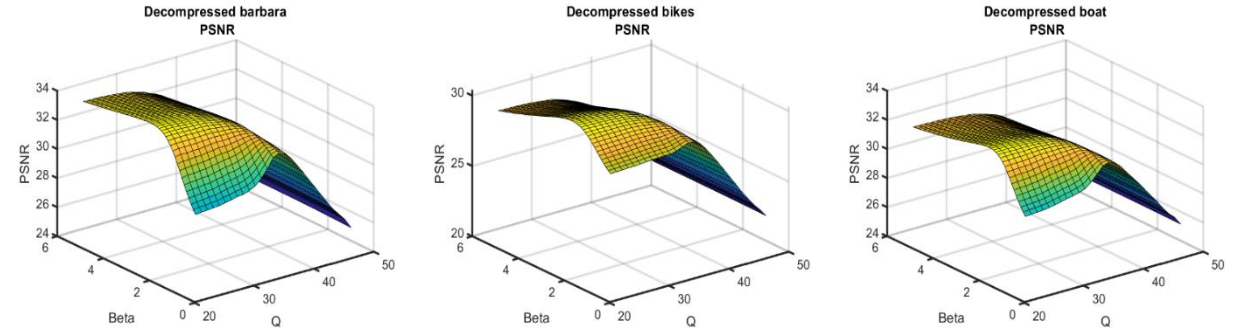
a b c

Fig. 2. Dependences of $PSNR_{pft}$ (after compression and filtering) on Q and β for three test images Barbara (a), Bikes (b), and Boat (c) corrupted by AWGN with noise variance equal to 50



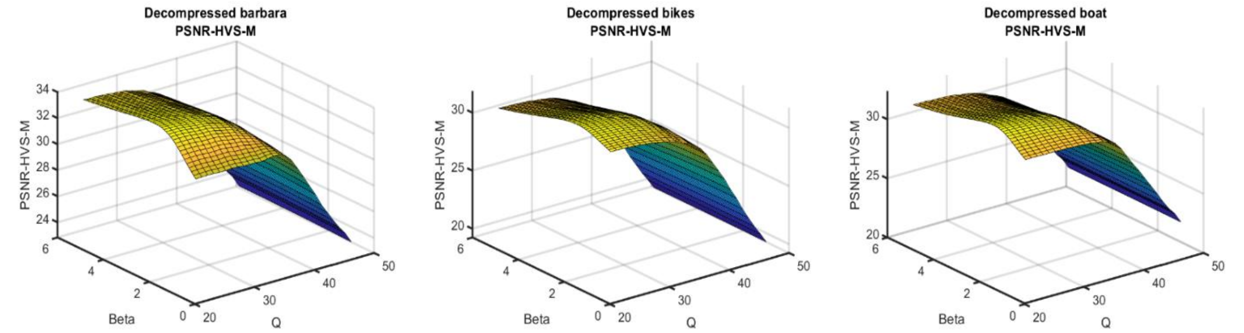
a b c

Fig. 3. Dependences of PSNR-HVS-M_{pft} (after compression and filtering) on Q and β for three test images Barbara (a), Bikes (b), and Boat (c) corrupted by AWGN with noise variance equal to 50



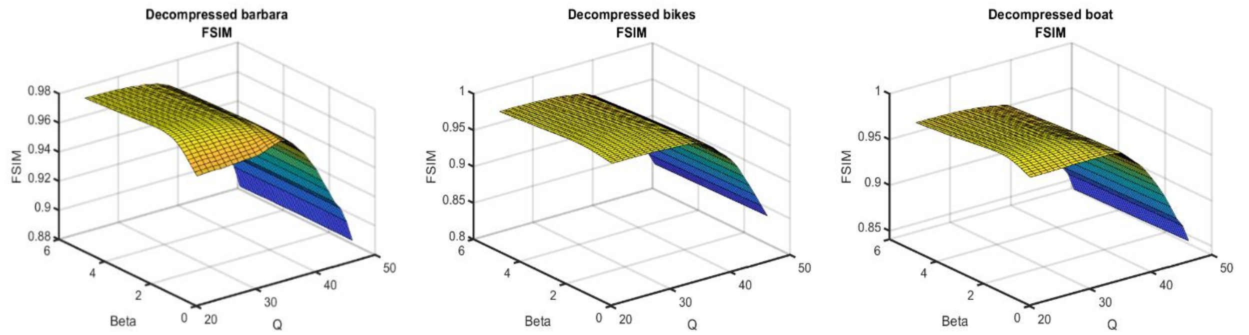
a b c

Fig. 4. Dependences of $PSNR_{pft}$ (after compression and filtering) on Q and β for three test images Barbara (a), Bikes (b), and Boat (c) corrupted by AWGN with noise variance equal to 200



a b c

Fig. 5. Dependences of PSNR-HVS-M_{pft} (after compression and filtering) on Q and β for three test images Barbara (a), Bikes (b), and Boat (c) corrupted by AWGN with noise variance equal to 200



a b c

Fig. 6. Dependences of $FSIM_{pft}$ (after compression and filtering) on Q and β for three test images Barbara (a), Bikes (b), and Boat (c) corrupted by AWGN with noise variance equal to 200

Table 1 – **Generalized data for PSNR**

Image	σ^2	δPSNR	$\delta PSNR_{pred}$	$PSNR_{p2}(Q_{OOP}-5)$	$PSNR_{p2}(Q_{OOP})$	$PSNR_{ct\ pred}$	$PSNR_{p2}(Q_{OOP}+5)$
Barbara	50	5.3	3.5	4.9	4.2	0.6	2.0
	100	7.3	5.1	6.7	5.7	1.9	3.0
	200	8.7	6.4	8.1	6.9	3.2	4.0
Bikes	50	2.7	2.0	2.3	1.5	-0.3	-1.0
	100	4.3	3.1	3.8	2.7	0.3	-0.1
	200	5.4	4.2	4.8	3.6	1.1	0.7
Boat	50	3.8	3.6	3.4	2.7	0.7	0.9
	100	5.9	5.4	5.3	4.4	2.3	2.3
	200	7.4	6.9	6.8	5.9	3.8	3.7

Analysis of data shows the following:

1) If δPSNR > 4 dB (e.g., see data for the test image Barbara, $\sigma^2 = 100$), then, most probably, all $PSNR_{p2}(Q_{OOP} - 5)$, $PSNR_{p2}(Q_{OOP})$, $PSNR_{p2}(Q_{OOP} + 5)$ are positive and it is possible to choose the option according to the priority of requirements, i.e. if a larger CR is desired

with simultaneous appropriate quality, then Q can be set up to $Q_{OOP} + 5$; otherwise Q can be set equal to Q_{OOP};

2) If 2 dB < δPSNR <4 dB (e.g., see data for the test image Bikes, $\sigma^2 = 50$), then it is not reasonable to use Q larger than Q_{OOP}; otherwise, compressed image quality is+ significantly worse than original;

3) If δPSNR < 2 dB, then it is reasonable to use Q equal to $Q_{OOP} – 5$ or $Q_{OOP} – 4$ with post-filtering with β smaller than 2.6 (e.g. 2.3),

4) Since $PSNR_{p2}(Q_{OOP}) > PSNR_{ct\ pred}$ (and the difference is of about 2–4 dB, this is clearly seen in Fig. 2 and 4), it is still reasonable to apply post-filtering for $Q \approx Q_{OOP}$;

5) $\delta PSNR \approx \delta PSNR_{pred}$, i.e. prediction is quite accurate although predicted values are smaller than true ones (note that we have used the method [26], which is the simplest but less accurate compared to more complex counterparts);

6) $PSNR_{p2}(Q_{OOP} -5)$ is only 0.4–0.6 dB smaller than δPSNR, i.e. quality of compressed and post-filtered images is high; meanwhile, $PSNR_{p2}(Q_{OOP} + 5)$ is by 3–4 dB smaller than δPSNR, i.e. quality degradation is significant.

If so, it is worth predicting δPSNR and it is able to serve for decision undertaking according to the recommendations given above. Prediction of OOP existence can be useful as well since it is able to provide additional data for decision undertaking.

And now we come to description how prediction can be carried out. It has been shown in [26] that the ratio between output MSE and noise variance has a rather strict dependence with a parameter $P_{2\sigma}$. This parameter is defined as probability that amplitudes of AC DCT coefficients in 8×8 pixel blocks are smaller than 2σ.

It is usually enough to have 500-1000 randomly placed blocks to determine $P_{2\sigma}$ with appropriate accuracy. For the BM3D filter, $\delta PSNR_{pred}$ is determined as $10\log_{10}(\sigma^2/MSE)$ where

$$MSE/\sigma^2 \approx -2.69(P_{2\sigma})^2+2.2P_{2\sigma}+0.36 \text{ [26].}$$

The ways for more accurate prediction are described in [30].

To predict $PSNR_{ct\ pred}$ (image quality after lossy compression), it is possible to use the same (previously obtained) parameter $P_{2\sigma}$ and the formula presented in the article [22]:

$$PSNR_{ct\ pred} = \frac{1.533\times10^4 \times P_{2\sigma} + 1.112 \times 10^4}{\left(P_{2\sigma}\right)^3 + 75.71\times\left(P_{2\sigma}\right)^2 - 6291\times P_{2\sigma} + 6139}. \quad (6)$$

Below in Fig. 7, we present some results of processing: the original image Barbara is given in Fig. 7, a, its noisy version for $\sigma^2 = 200$ is given in Fig. 7, b.

The image after lossy compression with $Q \approx Q_{OOP}$ is presented in Fig. 7, c whilst the image with lossy compression with $Q \approx Q_{OOP} – 5$ is given in Fig. 7, d.

Fig. 7. An example of the original image (a), distorted by noise (b), compressed with losses at $Q \approx Q_{OOP}$ (c), compressed with losses at $Q \approx Q_{OOP}$-5 (d), filtering result for $Q \approx Q_{OOP}$ (e) and filtering result for $Q \approx Q_{OOP}$-5 (f)

As one can see, lossy compression with $Q \approx Q_{OOP} - 5$ does not suppress noise significantly whilst compression in OOP leads to considerably noise reduction.

Images in Fig. 7, e and 7, f are post-filtered ones using the BM3D filter. After filtering, the following PSNR values have been obtained: 31.98 dB for OOP (CR = 14.21) and 33.18 dB for $Q \approx Q_{OOP} - 5$ (CR = 3.9). As one can see, the best result is provided for $Q \approx Q_{OOP} - 5$ with post-filtering (however, by the expense of smaller CR).

If a larger CR is of prime importance, a larger Q can be employed.

Conclusions

In this paper, we have considered applicability of post-filtering to improving the quality of compressed noisy images.

It has been shown that post-filtering is reasonable for $Q \le Q_{OOP}$ and, sometimes, for simple and middle complexity images and intensive noise, even for $Q \le Q_{OOP} + 5$.

When Q increases, filtering should be more "careful" – for $Q \le Q_{OOP} - 5$, optimal β is about 2.6, but for larger Q the optimal β decreases. A good compromise between quality and CR is provided for $Q \approx Q_{OOP} - 5$. Then, the quality of the compressed and the post-filtered images is almost the same as just the filtered image (without compression), but CR is significantly larger than for lossless compression (that produces CR that is only slightly larger than unity for noisy images irrespectively to their complexity).

We have also shown that improvement of image quality due to filtering can be quite accurately predicted and this allows deciding what compression parameter to apply.

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Received (Надійшла) 04.04.2024
Accepted for publication (Прийнята до друку) 24.07.2024

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Постфільтрація зашумлених зображень стиснутих із втратами та прогнозування її ефективності

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Анотація. **Об'єктом** дослідження є процес стиснення із втратами зображень, що спотворені шумом, та їх постфільтрація. **Предметом** дослідження є підхід до ефективної двоетапної обробки (стиснення та пост-фільтрація) для кращого портативного графічного кодера (BPG) та прогнозування її ефективності. **Мета** дослідження – проаналізувати характеристики ефективності розглянутого двоетапного підходу та запропонувати підхід до їх прогнозування. Використані **методи**: чисельне моделювання, регресія, статистичний аналіз. Отримані **результати**: 1) перевага розглянутого підходу полягає в тому, що він здатний забезпечити покращення якості стисненого зашумленого зображення за умови, що зображення стискається зі ступенем стиснення, меншим за той, який відповідає оптимальній робочій точці; 2) ефективність підходу залежить від кількох факторів, включаючи інтенсивність шуму, складність зображення, тип і параметри фільтра; 3) основні характеристики двоетапної процедури можна досить точно передбачити заздалегідь, що дозволяє запропонувати корисну інформацію для прийняття рішення про те, яке значення параметра кодера застосовувати; 4) це призводить або до покращення якості стисненого та обробленого зображення порівняно з його оригінальною версією, або, принаймні, до уникнення погіршення якості. **Висновки**: за результатами дослідження доцільно 1) спрогнозувати характеристики продуктивності двоетапної обробки; 2) адаптація обробки до складності зображення та інтенсивності шуму.

Ключові слова: стиснення зображення з втратами; контроль якості; шум; двоетапна обробка; прогнозування.