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ON STRANGE IMAGES WITH APPLICATION TO LOSSY IMAGE COMPRESSION

Single and three-channel images are widely used in numerous applications. Due to the increasing volume of such data, they must be compressed where lossy compression offers more opportunities. Usually, it is supposed that, for a given image, a larger compression ratio leads to worse quality of the compressed image according to all quality metrics. This is true for most practical cases. However, it has been found recently that images are called "strange" for which a rate-distortion curve like dependence of the peak signal-to-noise ratio on the quality factor or quantization step, behaves non-monotonously. This might cause problems in the lossy compression of images. Thus, the basic ***subject*** *of this paper are the factors that determine this phenomenon. The main among them are artificial origin of an image, possible presence of large homogeneous regions, specific behavior of image histograms. The main* ***goal*** *of this paper is to consider and explain the peculiarities of the lossy compression of strange images. The* ***tasks*** *of this paper are to provide definitions of strange images and to check whether non-monotonicity of rate-distortion curves occurs for different coders and metrics. One more task is to put ideas and methodology forward of further studies intended to detect strange images before their compression. The main* ***result*** *is that non-monotonous behavior can be observed for the same image for several quality metrics and coders. This means that not the coder but image properties determine the probability of an image to being strange. Moreover, both grayscale and color images can be strange, and both the natural scene and artificial images can be strange. This depends more on image properties than on image origin and number of channels. In particular, the percentage of pixels that belong to large homogeneous regions and image entropy play an important role. As* ***conclusions****, we outline possible directions of future research that, in the first order, relate to the analysis of images in large databases to establish parameters that show that a given image can be considered as strange.*

Keywords: *lossy compression; strange images; coders; quality metrics; rate-distortion curves.*

1. Introduction

Nowadays, imaging and images are widely used in everyday life (e.g., social networks, medical diagnostics, remote sensing, and other fields) [1-3]. Amount of images grows quickly, their average size increases as well due to several reasons as better spatial resolution and a larger number of channels (in remote sensing). This leads to necessity to compress images for their storage, transferring via communication links and dissemination.

There are lossless and lossy image compression techniques [4-6]. Visually lossless approaches are separately considered sometimes as well [7, 8]. Lossless compression is often inappropriate since it produces too small compression ratio (CR). Because of this, visually lossless and lossy compression techniques are widely used. They introduce inevitable distortions (losses) and an appropriate trade-off between the compressed image quality and CR has to be provided [8-12].

Then, one has to control introduced distortions that affect compressed image quality in one or another way. This can be done by iterative procedures like that one described in [13] or by predicting just noticeable distortions [8] or in some other way [14]. In any case, one directly or indirectly uses the so-called rate-distortion curves or their basic properties. Rate-distortion curves (RDCs) are dependences of some metric that characterizes compressed image quality on some parameter of a used coder that controls compression. Quality metric can be mean square error (MSE), peak signal-to-noise ratio (PSNR) or some visual quality metric as, e.g., SSIM [15] or PSNR-HVS-M (available for downloading from https://www.ponomarenko.info/psnrhvsm.htm). Parameter that controls compression (PCC) depends upon a coder used and this can be quality factor (QF) as in JPEG [16], bits per pixel (bpp) as in JPEG2000 or SPIHT [9, 10, 12], quantization step (QS) as in AGU (available at https://ponomarenko.info/agu.htm) and so on.

There are certain standard assumptions concerning RDCs [17-19]. They can be either monotonously increasing function as, e.g., PSNR on QF for JPEG or monotonously decreasing function as, e.g., PSNR or PSNR-HVS-M on bpp. Just these properties of RDCs allow proper changing (setting) of PCC in iterative or prediction based approaches to provide a desired quality of compressed images automatically, i.e. without human participation. Recall that just automatic setting of PCC is needed in most practical applications of lossy compression.

The aforementioned assumption on monotonicity of RDCs is valid for most images. However, it has been discovered recently that this assumption can be violated for

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some images with specific properties [20]. The main attention in [20] is paid to the fact that RDCs can be not monotonous for some images, compression techniques and metrics. However, a thorough analysis has not been carried out because of limited available volume of the conference paper.

Thus, the goal of this paper is to give definition of strange images, to analyze features of images that make them candidates to be strange, to determine coders and metrics for which strange images can be observed and to determine the directions of further studies.

The paper is organized as follows. The problem of appearance of strange images is defined, and its solution methodology is described in Section 2. An extended analysis of color “strange” images is described in Section 3. Finally, conclusions and directions for further studies are given in Section 4.

2. Problem statement and solution methodology

2.1. Problem statement

Let us recall typical properties of RDCs and give some examples. Suppose one has a set of several images to be compressed by a given coder. In experiments, RDCs can be obtained for each particular image by setting several values of PCC and determining values of a considered metric for them with further approximation of metric values for intermediate values of PCC (if PCC might have a limited size set of possible values like QF in JPEG or the adjustable parameter Q in better portable graphics (BPG) coder [21], then it is possible to obtain all values of the considered metric).

Figure 1 presents an example of such RDCs for 9 test grayscale images compressed by AGU coder for which QS serves as PCC.

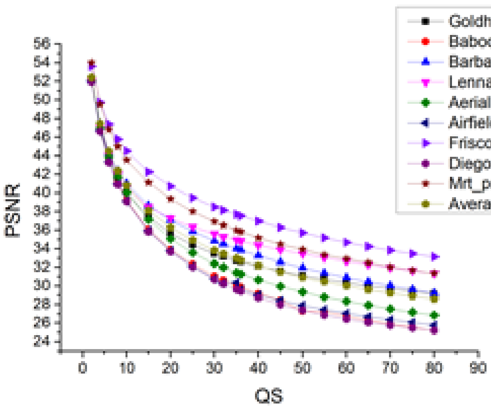


Fig. 1. RDCs PSNR vs QS for the AGU coder

As one can see, all RDCs, including the average one needed for the two-step procedure of providing a desired PSNR [14], are monotonously decreasing. One point is also worth mentioning. Since people usually suppose RDCs to be smooth, they often set a reasonably large step of PCC changing. The example in Fig. 1 shows that QS values were set as 5, 10, 15, …, 80 to cover the area of image quality under interest (PSNR values from about 26 to 54 dB) and only for QS from 30 to 35 we have analyzed more values of QS.

Figure 2 shows RDCs (PSNR vs QF) for a set of fifty MCL-JCI color images compressed by JPEG (available at http://mcl.usc.edu/mcl-jci-dataset). Mostly, RDCs obtained for all 100 possible values of QF are monotonously increasing functions. Meanwhile, some of them are not as smooth as the plots in Fig. 1. Moreover, there are a few plots with local minima and maxima although they do not appear themselves obviously. Note that if one has set QF as 5, 10, 15, …, 100 for getting these dependences, minima and maxima could not be noticed.

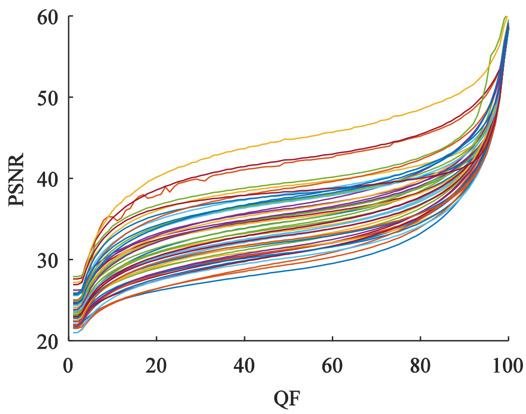
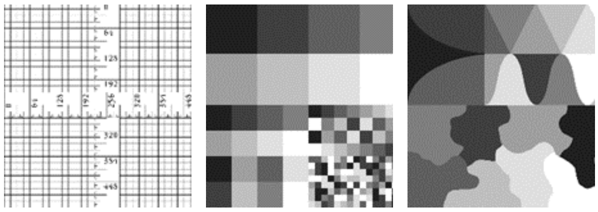


Fig. 2. RDCs PSNR on QF for a set of color natural scene images taken from the MCL-JCI database and compressed by JPEG

One more point is worth noting here. The examples in Figures 1 and 2 show that, for the same PCC, PSNR values are sufficiently different. For example, for QS=40 for the AGU coder (Fig. 1) PSNR values are from about 29 to 39 dB. Similarly, for QF=40 for JPEG (Fig. 2), PSNR values are from about 29 to 43 dB. This means that quality of compressed images is sufficiently different (at least, according to the PSNR metric). Then, to provide a desired quality (according to a chosen metric), one has to individually set PCC for each image depending on its properties (complexity, peculiarities of RDC behavior).

In [20], we have analyzed the images presented in Fig. 3. They have been compressed by the AGU coder. As it is seen, all these images are characterized by two peculiarities. They are of artificial origin and they have large homogeneous regions. The RDCs for them are given in Fig. 4. First, for images Texture #40 (Fig. 3,b), and Texture #42 (Fig. 3,c) the PSNR values for large QS (e.g., QS=80) are considerably larger than for other grayscale images (see the data in Fig. 4 and compare to the plots in Fig. 1). Second, for the test image Ruler

(Fig. 3,a), the RDC has local minima (for QS=65 and 75, see Fig. 4).



a b c

Fig. 3. The test images Ruler (a), Texture #40 (b), and Texture #42 (c)

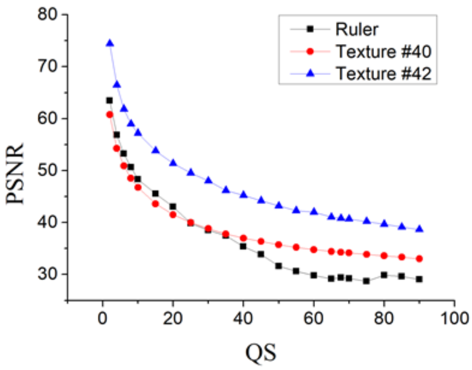


Fig. 4. RDCs PSNR vs QS for the AGU coder for three test images in Fig. 3

Then, Ruler is a strange image. We can define strange images in different ways. If PCC can fall into any positive value, we can state that an image can be considered "strange" according to a given metric if the corresponding RDC is not monotonous, e.g., has local minimum or local maximum as the RDC in Fig. 4 for the image Ruler. If PCC can fall only into fixed values, other definitions are possible. For example, if for a given image for a RDC of monotonously decreasing/increasing type there is such index i that

$$\mathrm{Metr}(i\text{-}1) < \mathrm{Metr}(i) \wedge \mathrm{Metr}(i) > \mathrm{Metr}(i+1), \qquad (1)$$

or

$$\mathrm{Metr}(i\text{-}1) > \mathrm{Metr}(i) \wedge \mathrm{Metr}(i) < \mathrm{Metr}(i+1), \qquad (2)$$

then this is "strange" image where Metr(i) is a used metric determined for an i-th value of PCC (such as PSNR in the previous examples).

Even stricter rules can be introduced. For example, an image can be considered strange if for a RDC there is such index i that

$$\mathrm{Metr}(i)\text{-}\mathrm{Metr}(i\text{-}1) > \Delta \wedge \mathrm{Metr}(i)\text{-}\mathrm{Metr}(i+1) > \Delta, \qquad (3)$$

or

$$\mathrm{Metr}(i)\text{-}\mathrm{Metr}(i\text{-}1) < \Delta \wedge \mathrm{Metr}(i)\text{-}\mathrm{Metr}(i+1) < \Delta, \qquad (4)$$

where Δ is some positive threshold value.

Thus, we have some initial observations about strange images. First, they might exist according to PSNR metric for both grayscale images compressed by AGU and color images compressed by JPEG. One question is do they exist for other coders and other metrics. An initial assumption is also that an image declared as strange usually contains large homogeneous region or regions. A third aspect relates to a question how to detect "strange" images in advance.

Before passing to the next subsection, we have to draw attention of a reader to the following fact. It is possible that local maxima (or minima) can appear in RDCs due to other reasons. In particular, we have detected several RDCs as those shown in Fig. 5. They take place when JPEG compression is applied to images that have been previously (in the past) compressed by JPEG with a rather large QF. We are not interested in studying such artifacts in our paper.

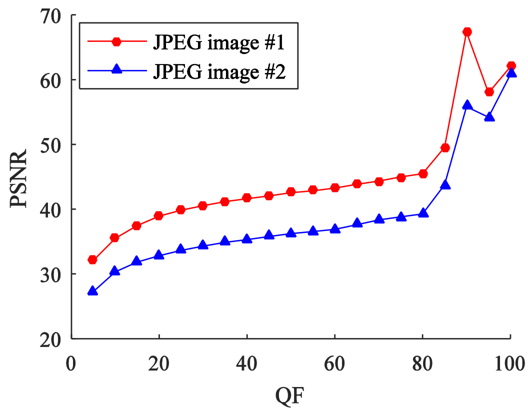


Fig. 5. RDCs for images where JPEG is applied to color images already (previously) compressed by JPEG

2.2. Solution methodology

If a "strange" image is detected for some metric and some coder, it is worth checking is this image strange for other coder(s) and quality metric(s). If we have detected a "strange" image, let us characterize its properties by entropy (at the first stage of analysis) since entropy is one of parameters that describe image complexity (properties) [21, 22]. These two rules determine our methodology of analysis at the initial stage.

So, let us look at RDCs PSNR-HVS-M on QS for the coder AGU applied to three grayscale images in Fig. 3. Recall here that PSNR-HVS-M is expressed in dB and this visual quality metric takes into account two important peculiarities of human vision system (HVS) – less sensitivity to distortions in high spatial frequencies and masking effect. For PSNR-HVS-M, distortion visibility threshold is about 40 dB.

The RDCs PSNR-HVS-M vs QS and QF for the AGU and JPEG coders are presented in Fig. 6. As it is see from Fig. 6,a, the RDC for the image Ruler has local minimum for QS≈65 and local maximum for QS≈80.

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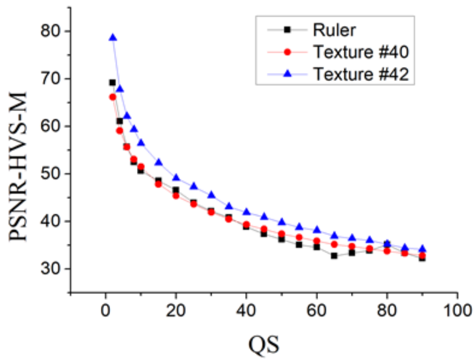
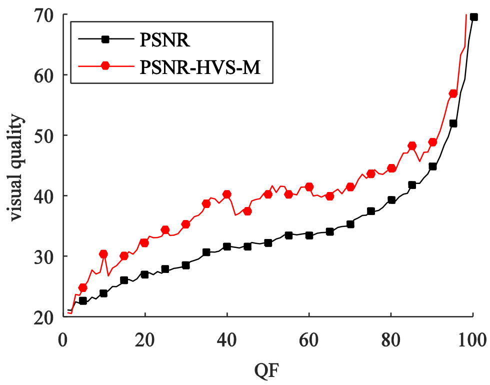
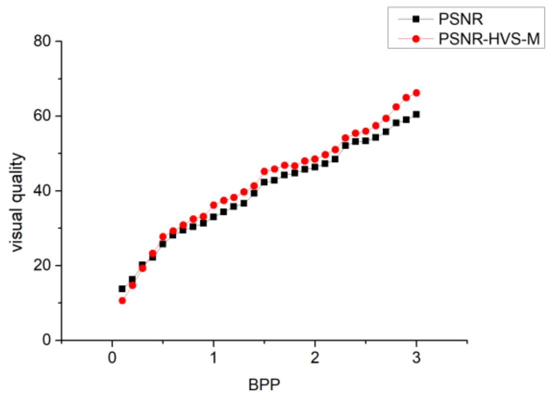
Furthermore, Fig. 6,b shows the RDCs for the image Ruler compressed by JPEG. According to both visual quality metrics, PNSR and PSNR-HVS-M, this image is strange. Finally, this means that if an image is “strange” according to one quality metric, it is quite probable that it can be also “strange” according to another metric although coordinates of local extrema of the corresponding dependences might not coincide.



a



b



c

Fig. 6. Dependences of PSNR-HVS-M on QS for the coder AGU applied to grayscale images in Fig. 3 (a), RDCs for the image Ruler compressed by JPEG (b) and RDCs for the image Ruler compressed by SPIHT (c)

It should be noted in Fig. 6,b that if the PSNR is determined with a QF step of 5, the Ruler image is not strange. Also, note that for the image Ruler the entropy is equal to 0.5, for the image Texture #40 the entropy equals to 2.9994, and for the image Texture #42 the entropy is equal to 2.9833. This means that, while searching for potential candidates to be “strange” images it is worth paying attention to entropy. In addition, Fig. 6,c also shows RDCs for the image Ruler compressed by SPIHT. Although these curves are not smooth enough, the image Ruler in this case is not “strange” according to our definition. Probably, “strange” images happen more often for DCT-based coders than for wavelet based ones. However, this assumption has to be checked in the future.

Above, we have assumed that images with low values of entropy can be “strange”. To check this assumption, we have carried out a special experiment. It is known that for noisy images entropy is usually larger than for almost noise-free ones. Because of these, we have generated a specific noise-free image given in Fig. 7,a and artificially added additive white Gaussian noise (AWGN) to it with standard deviations (STD) equal to 3 and 6 with obtaining the images in Figures 7,b and 7,c, respectively. Note that the entropy for the image in Fig. 7,a is equal to 1, for the image in Fig. 7,b it is equal to 4.64, and for the image in Fig. 7,c the entropy equals to 5.63 (for most natural scene images the entropy is in the limits from 6 to 7.5).

a b c

Fig. 7. Test grayscale images used in experiments: noise-free image (a) and noisy images with AWGN standard deviation equal to 3 (b) and 6 (c)

The dependences obtained for JPEG applied to images in Fig. 7 are presented in Fig. 8. As one can see, all three images are “strange” according to definitions (1) and (2). Meanwhile, there is an essential difference. Whilst there are numerous local minima and maxima for the dependence in Fig. 8,a obtained for noise-free image in Fig. 7,a, the amount of local minima and maxima decreases if noise is added and its standard deviation increases. The presented results also show the following. In the paper [20] it was assumed that entropy about 3 can be a threshold for discrimination of “strange” and “conventional” images. This assumption is wrong since images with larger entropies can be “strange” as well. This shows that detection of “strange” images is not an easy task and it has to be paid special attention.

One more assumption that has been put forward in

[20] was that images containing quite large percentage of pixels that belong to some background or homogeneous regions could be “strange”. To check this hypothesis, we have considered three grayscale images with aforementioned properties presented in Fig. 9 (available at https://sites.google.com/site/subjectiveqa/). The image in Fig. 9,a has entropy equal to 4.19, the image in Fig. 9,b is characterized by entropy equal to 1.98, and the image in Fig. 9,c has the entropy equal to 4.66.

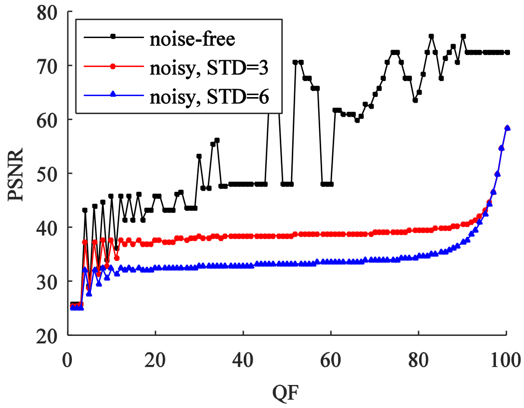


Fig. 8. Dependences PSNR on QF compressed by JPEG for the images in Fig. 7

a

b c

Fig. 9. Grayscale images with a large percentage of pixels that belong to background

These images have been compressed by JPEG and the corresponding RDCs are depicted in Fig. 10, respectively. As one can see, these images are not “strange”, at least, for JPEG and according to PSNR. Note here that the entropy for the image in Fig. 9,b is quite small but it cannot be related to “strange” images since its RDC behaves in traditional (expected) manner.

This means one more time that entropy cannot be used as the indicator that an image is “strange”. At least, we need another parameter or several parameters that are able to discriminate “strange” and “conventional” images. Maybe, entropy can be one of such parameters but not the only one.

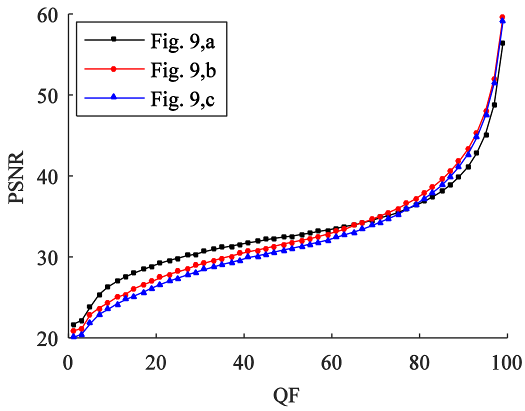


Fig. 10. RDCs PSNR on QF for JPEG applied to images in Figures 9,a, 9,b, and 9,c.

Finally, let us also analyze “dark” HDR images taken from the database available at the link http://resources.mpi-inf.mpg.de/hdr/quality/. The images are given in Fig. 11. The entropy for the image in Fig. 11,a equals to 3.02, for the second image it is equal to 5.67. The RDCs for these images compressed by JPEG are represented in Fig. 12. In the first case, the image in Fig. 11,a can be related to the class of “strange” ones whilst, in the second case, the RDC behaves in traditional manner and is monotonous.

a b

Fig. 11. Two “dark” HDR images

One observation is that the entropy value for the “strange” image is smaller than for conventional image. Thus, smaller values of entropy, in general, evidence in favor of probability of the corresponding image to be “strange”.

To partly explain why local maxima and minima of PSNR appear, let us consider an extreme case of fully homogeneous image of the constant level C.

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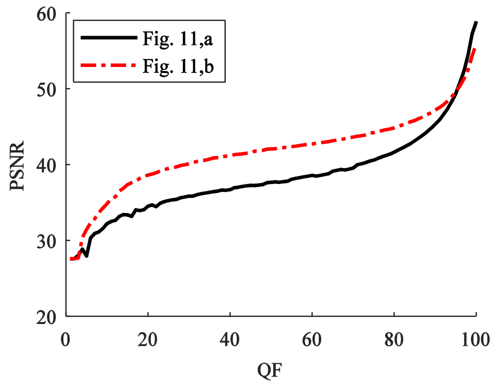


Fig. 12. The RDCs PSNR on QF for images in Fig. 11 compressed by JPEG

Suppose it is compressed by JPEG with $QS=QS_0$ for DCT coefficient D(0,0) in each block or by the AGU coder (recall that the AGU coder is based on 2D DCT in 32x32 pixel blocks). Since we deal with fully homogeneous image, all other DCT coefficients in blocks are equal to 0 before quantizing, after quantizing, and after decompression. Thus, these DCT coefficients have no impact on errors introduced by lossy compression. Only quantization of D(0,0) DCT coefficient plays the role. Then after quantizing one gets $[C/QS_0]$ where [] means rounding to the nearest integer. At decompression stage, one gets

$$C_{dec} = QS_0 \times [C/QS_0] \quad (5)$$

and C_{dec} might differ from C by up to QS_0. For example, if C=45, then no errors are introduced for QS_0 equal to 3, 5, 9, 15, and 45, but the difference between C and C_{dec} can be, e.g., equal to 5 for QS_0 equal to 20 or 25. Radical jumps of C_{dec} are possible if QS_0 changes by 1. For example, C_{dec} is equal to 90 for QS_0=90 and it jumps to 0 for QS_0=91.

Then, some preliminary conclusions are possible. First, the occurrence of PSNR irregularity (non-monotonicity) in JPEG compressed images as well as images compressed by other DCT-based coders is expected. It might occur in images that have uniform (or near-uniform) blocks. Irregularities are a consequence of DCT-coefficient rounding and the definition of PSNR (where PSNR is not bounded from the upper side, i.e. it can go to infinity). Second, for uniform blocks with constant gray level values, MSE minimum positions can be determined on the basis of quantization coefficients (matrices). The positions of local maxima can be determined in a similar way. Third, appearance of irregularity mainly depends on the presence of a large area has a constant (or almost constant) gray level value. Entropy can be a rough indicator of irregularity. Fourth, achieving the target (desired) PSNR value for images compressed by JPEG or other DCT-based coders can be problematic if the source images have large uniform regions.

3. Analysis for color images and discussion

We have already demonstrated in Fig. 2 that color images can be “strange” as well. In this Section, we consider color images more in detail.

First, in the paper [23], fifty color images have been used in experiments concerning just noticeable differences due to lossy compression. One of these images is presented in Fig. 13 and it contains a large “dark” background. Dependence of PSNR on QF for JPEG for the image in Fig. 13 is given in Fig. 14. Obviously, it contains several local minima and maxima and, thus, this image can be treated as “strange”. Thus, the preliminary conclusion is that color images can be “strange” as well and, probably, this might happen if an image contains a large homogeneous background.

Fig. 13. An example of color image with large “dark” background

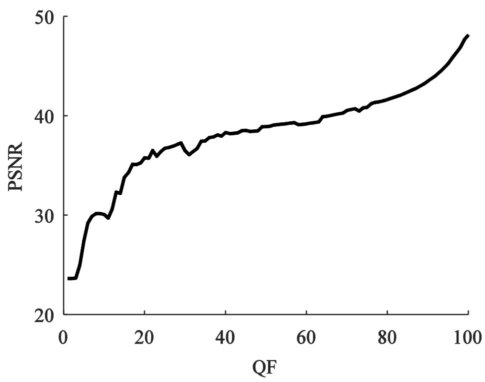


Fig. 14. Dependence PSNR on QF for the image in Fig. 13 compressed by JPEG

Analysis of RDCs has been carried out for tens of color images from SPAQ database (available at https://github.com/h4nwei/SPAQ). Fig. 15 shows two of detected “strange” images. The corresponding RDCs are represented in Fig. 16. In both cases, there are numerous local minima and maxima.

Both images in Fig. 15 have large homogeneous regions. To check the hypothesis that the presence of large homogeneous regions in color images can be the reason of these images to be “strange”, an additional artificial 512x512 image has been created, Fig. 17,a (the corresponding RGB color triplets are provided in the image).

a b

Fig. 15. Examples of detected “strange” images in the SPAQ database

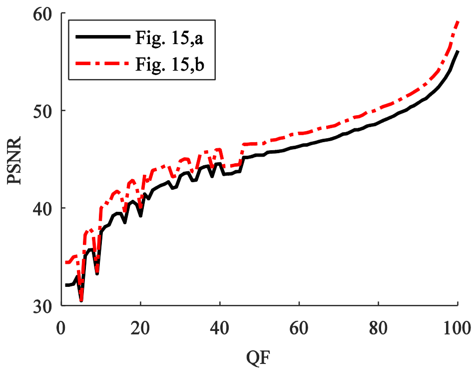


Fig. 16. Dependences of PSNR on QF for the image in Fig. 15,a and the image in Fig. 15,b compressed by JPEG

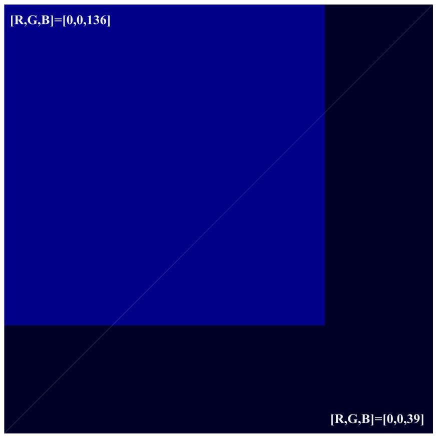
The RDC for it is represented in Fig. 17,b for JPEG. Multiple minima and maxima are observed and the image can be treated as “strange”. More analysis for this image can be found in [20].

Note that for the AGU coder applied component-wise and in 3D manner, the image in Fig. 17,a is “strange” as well. Thus, we can conclude that “strange” images might happen among color ones compressed by different DCT-based coders.

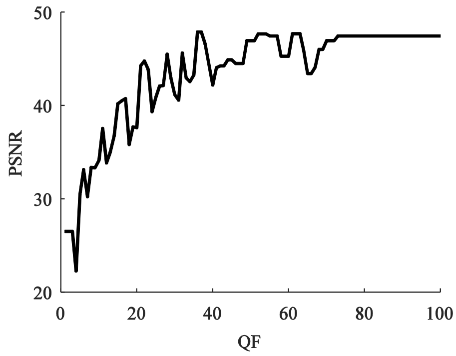
4. Conclusions

In this paper, we have defined and considered the images called “strange” since rate-distortion curves for them are non-monotonous and might contain one or multiple local maxima or minima. This makes problematic providing a desired quality for such images because the corresponding algorithms might fall into local minima or maxima, rate-distortion curve derivative values might have jumps and so on.

Our analysis has shown the following. Images defined as “strange” can be grayscale and color, they can be “strange” according to PSNR (MSE) and visual quality metrics. Most often a “strange” image contains a large homogeneous region or regions. Image entropy has a certain relation to probability of an image to be “strange” but this relation is not so strict as it has been stated in [20]. At least, comparison of image entropy to a certain threshold does not allow reliable discrimination of images into “strange” and “not strange”.



a



b

Fig. 17. Artificial color image (a) and dependence of PSNR on QF for this image compressed by JPEG (b)

Keeping this in mind, we see the following directions of further studies:

– to analyze large image databases in an automatic manner for searching the “strange” images;

– to look for parameters (image characteristics) that are able to reliably discriminate images into “strange” and conventional where calculation of these parameters takes considerably less time than compression itself;

– to analyze other DCT-based coders as, e.g., BPG as well as wavelet based coders as JPEG2000 (or SPIHT) or those based on atomic wavelets [24];

– to study how “strangeness” of images influences other operations of their processing as, e.g., segmentation [25].

Contributions of authors: conceptualization – **Vladimir Lukin**, **Boban Bondzulic**; methodology – **Boban Bondzulic**, **Vladimir Lukin**; formulation of

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tasks – **Boban Bondzulic**, **Vladimir Lukin**; analysis – **Fangfang Li**, **Dimitrije Bujakovic**; development of model – **Fangfang Li**, **Dimitrije Bujakovic**; software – **Dimitrije Bujakovic**, **Fangfang Li**; verification – **Dimitrije Bujakovic**, **Fangfang Li**; analysis of results – **Vladimir Lukin**, **Boban Bondzulic**; visualization – **Dimitrije Bujakovic**, **Fangfang Li**; writing – original draft preparation – **Vladimir Lukin**, **Boban Bondzulic**; writing – review and editing – **Vladimir Lukin**, **Boban Bondzulic**.

All the authors have read and agreed to the published version of the manuscript.

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ЩОДО ДИВНИХ ЗОБРАЖЕНЬ У ЗАСТОСУВАННІ ДО СТИСНЕННЯ ЗОБРАЖЕНЬ З ВТРАТАМИ

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Одно- та триканальні зображення широко використовуються у багатьох додатках. Внаслідок зростання об'єму таких даних їх необхідно стискати, при цьому стиснення з втратами забезпечує більш широкі можливості. Зазвичай припускається, що для даного зображення більший коефіцієнт стиску призводить до гіршої якості у відповідності до будь-яких метрик. Це справедливо для більшості практичних випадків. Втім нещодавно було виявлено, що існують так звані "дивні" зображення, для яких крива залежності спотворень від ступеня стиснення як залежність пікового відношення сигнал-шум від фактору якості чи кроку квантування поводиться немонотонно. Це може призводити до проблем під час стиснення зображень з втратами. Тож основним **предметом** статті є фактори, що визначають згадане явище. Головними з них є штучне походження зображення, можлива наявність однорідних ділянок великого розміру, специфічна поведінка гістограм зображень. Основною **метою** є розглянути та пояснити особливості стиснення дивних зображень з втратами. **Завдання** статті – надати визначення дивних зображень та перевірити, чи немонотонність залежностей спотворень від рівня стиснення має місце для різних кодерів та метрик. Ще одне завдання – надати ідеї та методологію наступних досліджень, що спрямовані на виявлення дивних зображень до їх стиснення. Головний **результат** полягає в тому, що немонотонна поведінка може спостерігатись для того ж самого зображення для різних метрик якості та кодерів. Це означає, що не властивості кодера, а властивості зображення визначають ймовірність того, що зображення є дивним. Більш того, дивними можуть бути як зображення в градаціях сірого, так і кольорові, як зображення натуральних сцен, так і штучні. Це і більшому ступені залежить від властивостей зображення, ніж від його походження та кількості каналів. Зокрема, важливу роль грають відсоток пікселів, що належать до однорідних ділянок, та ентропія. Як **висновок**, нами надаються можливі напрямки майбутніх досліджень, які, в першу чергу, відносяться до аналізу зображень у базах великого розміру з метою встановити параметри, які вказують, що дане зображення може бути дивним.

Ключові слова: стиснення з втратами; дивні зображення; кодери; метрики якості; криві спотворення – ступінь стиснення.

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