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ANALYSIS OF TWO-STEP APPROACH FOR COMPRESSING TEXTURE IMAGES WITH DESIRED QUALITY

A task of lossy compression of remote sensing and other types of images with providing the desired quality is considered. Quality is mainly characterized by the peak signal-to-noise ratio (PSNR) but visual quality metrics are briefly studied as well. Potentially, a two-step approach can be used to carry out a compression with providing the desired quality in a quite simple way and with a reduced compression time. However, the two-step approach can run into problems for PSNR metric under conditions that a required PSNR is quite small (about 30 dB). These problems mainly deal with the accuracy of providing a desired quality at the second step. The paper analyzes the reasons why this happens. For this purpose, a set of nine test images of different complexity is analyzed first. Then, the use of the two-step approach is studied for a wide set of complex structure texture test images. The corresponding test experiments are carried out for several values of the desired PSNR. The obtained results show that the two-step approach has limitations in the cases when complex texture images have to be compressed with providing relatively low values of the desired PSNR. The main reason is that the rate-distortion dependence is nonlinear while linear approximation is applied at the second step. To get around the aforementioned shortcomings, a simple but efficient solution is proposed based on the performed analysis. It is shown that, due to the proposed modification, the application range of the two-step method of lossy compression has become considerably wider and it covers PSNR values that are commonly required in practice. The experiments are performed for a typical image encoder AGU based on discrete cosine transform (DCT) but it can be expected that the proposed approach is applicable for other DCT-based image compression techniques.

Keywords: *two-step approach; lossy compression; desired accuracy; complex texture image.*

Introduction

With improvement of image acquisition technologies, information contained in images increases and becomes more abundant. This assists users to solve many practically valuable tasks as Earth surface monitoring from aerospace carriers, intelligent map navigation, intelligent medical treatment, target recognition and many others. For many modern applications, there is a tendency to increase imaging system resolution and, respectively, the number of image pixels. In turn, then acquired images occupy more storage space and more time is needed to transfer them via communication lines with a limited bandwidth (e.g. from a satellite to on-land center of remote sensing data processing and dissemination). Then, image compression can be a useful way out [1].

It is known [2] that image compression can be lossless and lossy. The latter one is able to provide a considerably higher compression ratio (CR) than the best lossless compression. This means that, due to lossy compression, more storage space can be saved and more time can be saved when data are transferred. This is very important in practical situations where real-time performance is often required.

However, under a high compression ratio, it is inevitable that image distortions are introduced and some part of useful information can be lost. Then, some trade-off should be found between a compressed image quality and a produced CR [3]. Besides, image quality in lossy image compression has to be described (quantitatively assessed) using some adequate (application or service oriented) quality metrics [4]. An aforementioned trade-off can be reached if: a) an adequate metric is available; b) a tool (algorithm) for quality variation is available; c) a method for providing a desired quality with an appropriate accuracy is available and it is able to work quickly enough. In other words, one has to provide high computational efficiency, high reliability and accuracy of an approach to providing a desired quality of compressed images.

Many related studies have been carried out and some progress has been reached. In particular, iterative compression methods [5] can gradually approach the expected value of a used metric and achieve high accuracy that can be preset. Recall that, for iterative techniques, a considered image is compressed and decompressed multiple times with calculation of a chosen quality metric after each decompression, comparison of a metric current value to the desired one and adjusting a parameter that controls compression (PCC) appropriately (to move towards the desired metric value at the next step). Depending upon a coder used, quantization step (QS), scaling factor, quality factor or bpp (bits per pixel) can serve as PCC.

An obvious drawback of iterative approach is that the number of iterations is uncertain, it can vary in a rather wide limits depending upon a used algorithm of PCC changing, image properties and present accuracy of metric providing. Then, iterative compression might consume a lot of time and computing resources [5]. A positive feature of the iterative compression is that it practically guarantees reaching a desired accuracy of quality providing.

Another way to providing a desired quality in lossy compression is to extract a part of image information (statistics) as a basis for predicting compressed image quality, and then to compress the image without any iterations based on prediction and a recommended PCC. Such a non-iterative compression requires fewer computing resources, but is often unable to provide a sufficient accuracy [6].

A compromise solution for lossy compression can be a recently proposed two-step method [7]. At initial stage, it uses one compression/decompression using a starting PCC with metric calculation. Then, a final PCC is calculated using linear approximation and employing averaged rate-distortion curves obtained in advance. After this, the image is compressed using the final PCC.

Through the two-step compression method, the compression process has simplified and become faster. In some practically important situations. its accuracy is acceptable [7]. However, through in-depth research, it has been shown that if one needs to provide the desired quality characterized by peak signal-to-noise ratio (PSNR) about 30dB… 35dB or smaller, the accuracy radically decreases and becomes inacceptable. This happens more often if a compressed image has a complex structure. Meanwhile, complex structure (highly textural) images are ubiquitous in remote sensing imaging [8], industrial [9], and intelligent medical-assisted diagnostic applications [10]. Texture features are of great significance in image classification and automatic recognition [8].

The goal of this paper is to study the compression performance of complex texture images mainly employing PSNR as quality metric, to analyze the results and to give the limitations of the two-step method in practical applications. A correction scheme is proposed to improve the accuracy of quality providing for the two-step method after correction. The AGU encoder used in our experiments is an encoder based on discrete cosine transform (DCT) [11].

The organization of the paper is as follows. The basic peculiarities of the two-step method are introduced in the second Section. Analysis of the visual quality assessment results is given in the third Section. The fourth Section mainly involves the testing results for highly textural images. Their thorough analysis is done. In Conclusion, the revised two-step method is summarized, and suggestions for practical use of the two-step method are given.

Basic peculiarities of the two-step approach

As it has been already mentioned, the recently proposed two-step method of image compression consists of two stages. The first one is preliminary image compression/decompression with a “rough” quantization step. The goal of the first stage is to compress our image with providing a value of a considered metric rather close to a desired value. The problem here is that performance characteristics of any method of lossy compression depend upon many factors, in the first order, image complexity.

The term image complexity is widely used in image processing although it has not been strictly specified yet. So, let us try to explain it verbally by several examples. It is a known fact in lossless compression [10] that an attained CR varies in certain limits depending upon an image lossless compression is applied to. There are images with “unpredicted” or “hardly predictable” structure that are compressed with CR close to unity. These are images with many “locally active areas” as edges, details, and/or textures. Similarly, there are images for which efficient denoising is impossible [12]. Again, these are images with high percentage of pixels that belong to locally active areas.

Coming back to lossy compression, we can state that for complex structure images either PSNR is smaller if the same CR is provided (or the same PCC is used) or CR is smaller if the same PSNR is provided. To prove this, Fig. 1 presents two examples of the so-called rate-distortion curves – dependences of PSNR on QS for the coder AGU for which QS serves as PCC. These dependences (Fig. 1) have been obtained for two test remote sensing images - Frisco and Diego – that are presented in Fig. 2 and which are good example of simple and complex structure images, respectively. As one can see, PSNR values for a given QS can differ by several dB.

Taking this into account, the proposition in [7] was to apply some “good” initial QS at the first stage.
Because of this, the method [7] is based on using the average rate-distortion curve for trend prediction and QS setting. In fact, the average distortion curve provides appropriate preconditions for calculating the initial (rough) value of any PCC in general and QS for AGU in the considered particular case. The method of obtaining the average rate-distortion curve is explained below.

Let us select a certain number of test images as basic ones (nine images listed in Table 1 have been used at the experimental stage, which can be more in practical applications). For each image, the quality metric dependence on QS has been obtained. Then, data for each QS have been averaged providing an approximation of average distortion curve. A part of experimental data is shown in Table1 starting from very small and ending by very large QS values.

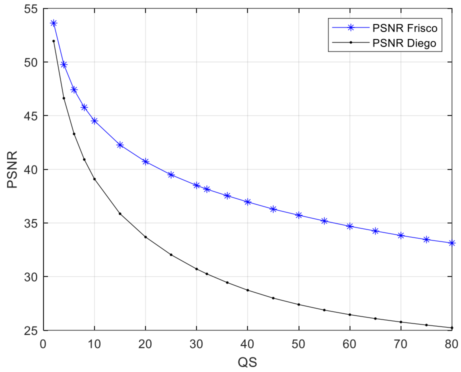

Fig. 1. Dependences of PSNR on QS for two test images compressed by the AGU encoder

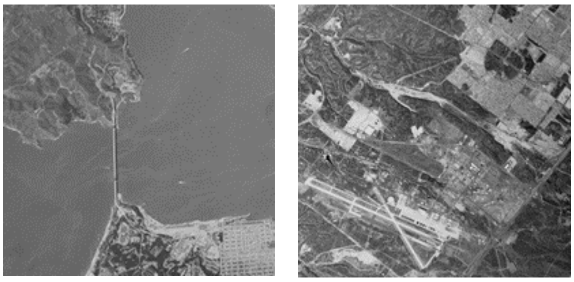

Fig. 2. Test images Frisc o and Diego

The considered set of test images contains four ones commonly used in image processing. In addition, four typical test remote sensing images and one medical image have been added. The reason for this is our hope that these test images are able to represent a wider field.

Analysis of data in Table 1 shows the following. When QS is small (QS <10), PSNR changes (reduces) drastically, so the QS changing step is set to 2, and when QS is relatively large, PSNR changes smoothly (slowly), so the step of its changing is set to 5. Comparison of PSNR values for QS=75 shows that they can differ from each other by almost 10 dB being the largest for simple structure test images and the smallest for complex structure ones.

Among data in Table 1, there is the AVERAGE line. The corresponding data allow determining derivative for average rate distortion curve (Fig. 3) that represents the trend and is exploited at the second stage of the two-step procedure. The trend shown in Figure 3 is very obvious. As QS value increases, the corresponding PSNR values become smaller, and the change in the derivative absolute value is similar.

Table 1

Experimental data of PSNR dependence on QS

QS value	**2**	**4**	**…**	**75**	**80**
Goldhill	51.996	46.834	…	29.4297	29.145
Baboon	51.953	46.667	…	25.5437	25.200
Barbara	52.065	47.150	…	29.6363	29.240
Lenna	52.041	47.020	…	31.6323	31.345
Aerial	52.063	46.998	…	27.1821	26.858
Airfield	52.043	46.714	…	26.0693	25.791
Frisco	53.626	49.755	…	33.4553	33.127
Diego	51.949	46.622	…	25.4872	25.227
Mrt_prepared	54.001	49.515	…	31.6745	31.363
average	52.415	47.475	…	28.9011	28.588
derivative	-2.470	-1.498		-0.06245	

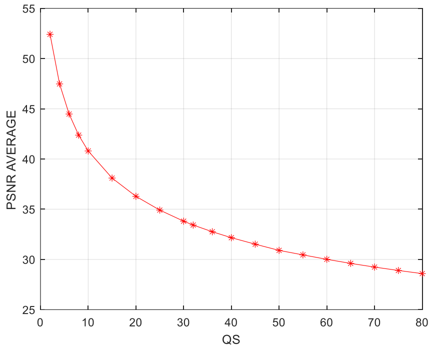

Fig. 3. PSNR average distortion curve

After the average distortion curve is obtained, we can first use it to calculate the initial value of QS. For example, let us provide $PSNR_{des}$=35 dB for the image Goldhill. According to average data in Table 2, it can be estimated that QS≈25, but the following calculations can be made for getting a better estimate of QS_{init}:

$$QS_{init} = QS_{est} + \frac{PSNR_{det} - PSNR_{ave}}{M'}, \qquad (1)$$

where QS_{est} is the value estimated from the average distortion data, $PSNR_{ave}$ is the average PSNR value corresponding to the estimated QS_{est}. M' is the derivative of the corresponding QS_{est}. Then, it equals 24.6064.

Table 2

Average data of PSNR dependence on QS

QS value	…		15	20	25	…
average	…		38.10263	36.2837	34.91293	…

The compressor can be run first time using QS_{init}, The $PSNR_{init}$ can be obtained, it equals 34.503dB. Then, at the second stage, calculate QS_{des} from the values obtained (QS_{init}, $PSNR_{init}$, $PSNR_{des}$, derivative):

$$QS_{des} = QS_{init} + \frac{PSNR_{des} - PSNR_{init}}{M'}. \quad (2)$$

Then, one has to run the compressor the second time setting QS_{des}=22.3587. the provided $PSNR_{prov}$ occurs to be equal to 35.0117dB, the error is less than 0.02dB. This example shows that if the rate-distortion curve for a given image is close to average rate distortion curve, one can expect that the two-step procedure will be able to improve accuracy of PSNR providing.

However, particular images might have rate-distortion curves (see Fig. 1) that differ from the average curve (Fig. 3), This leads to the fact that for the images Frisco and Diego, the errors of providing $PSNR_{des}$ = 35 dB are 1.246 dB and 2.794 dB, respectively. This is less than after the first stage but these errors are not appropriate. Such errors show that different accuracy of providing PSNR takes place and this is reflected in appearance of compressed images.

In order to understand this, some comparative experiments are necessary. In visual evaluation, let us employ three visual quality evaluation metrics, namely PSNR, PSNR-HVS, and PSNR-HVS-M. The latter two metrics take into account human visual system (HVS), and these visual quality metrics have been shown in the paper [8] to work well with the two-step method.

The comparison test results for Airfield image are shown in Fig. 4. The similarity of images in Fig. 4, a and Fig. 4, b is very high, some light differences can be found (the parts marked in blue), while one can more easily find some differences between images in Fig. 4, a and Fig. 4, c (these parts are marked in red).

a)

b)

c)

Fig. 4. Comparison of images: a, QS=30, PSNR =30.7564dB; PSNR-HVS = 30.1088dB; PSNR-HVS-M = 34.7141dB; CR = 7.0329; b, QS=35, PSNR =29.7700dB; PSNR-HVS =28.9909dB; PSNR-HVS-M =33.2661dB; CR = 8.5991; c, QS=40, PSNR = 29.0365dB; PSNR-HVS =28.0836dB; PSNR-HVS-M = 32.1077dB; CR =10.1689

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In this way, analysis of these images and the corresponding metrics' values allows drawing the following conclusions: when difference of PSNR values (ΔPSNR) is less than 1dB, the image difference is not obvious, but when ΔPSNR is greater than or equal to 1.5dB, the image difference can be easily observed.

Analysis of quality providing for two-step lossy compression approach

In [7], the results for the two-step compression method are analyzed for the set of test images (used in obtaining the average distortion curve). Three sets of data have been obtained for PSNR for three values of $PSNR_{des}$, namely, 34 dB, 37 dB, and 40 dB. It was found from the results that the proposed two-step procedure worked well enough if it was desired to provide PSNR larger than 37 dB, but the error of providing the desired PSNR occurred to be too large for $PSNR_{des}$ smaller than 35……37 dB [7].

To better understand how the two-step method works and what are the arising problems, consider the cases of $PSNR_{des}$ equal to 35 and 30 dB in more detail. Table 3 presents data obtained for $PSNR_{des}$=35dB. The lower line presents variance values of $PSNR_{init}$ and $PSNR_{prov}$. It is seen that, due to the second step, variance is significantly reduced compared to one step compression. It works well for simple and middle complexity images (consider data for such test images as Lenna, Barbara, Goldhill). However, there are four test images for which the error of providing $PSNR_{des}$ is greater than 1 dB. This means that people can clearly see the difference when looking at the corresponding images (recall the comparison in Section 2).

Table 3
Statistics and parameters of providing $PSNR_{des}$=35dB

Test image	QS_{init}	$PSNR_{init}$	ΔQS	QS_{rec}	$PSNR_{prov}$
Goldhill	24.6	34.503	-2.2476	22.358	35.0117
Baboon	24.6	32.4512	-11.526	13.079	37.1222
Barbara	24.6	35.9636	4.3578	28.964	35.0604
Lenna	24.6	36.3968	6.3169	30.923	35.4641
Aerial	24.6	33.6942	-5.9054	18.701	35.5482
Airfield	24.6	32.2547	-12.415	12.191	38.6067
Frisco	24.6	39.574	20.6781	45.284	36.2463
Diego	24.6	32.1536	-12.868	11.738	37.794
Mrt_prepared	24.6	38.0092	13.609	38.215	35.4429
Variance		7.1179			1.6761

Consider now the data for $PSNR_{des}$=30 dB. Recall here that for the cases PSNR about 30 dB and less the distortions introduced by lossy compression can be clearly observed and the image quality is quite poor. The obtained data are presented in Table 4. Analysis shows the following. First, variance values for both $PSNR_{init}$ and $PSNR_{prov}$ have sufficiently increased and become practically equal. Second, the number of images with an error larger than 1 dB has risen to 5 out of 9. This shows that the two-step method cannot provide appropriate accuracy of producing a desired PSNR when $PSNR_{des}$ is about 30 dB. Again, the largest errors are observed for highly textural images as Baboon, Airfield, Diego.

Table 4
Statistics and parameters of providing $PSNR_{des}$=30dB

Test image	QS_{init}	$PSNR_{init}$	ΔQS	QS_{rec}	$PSNR_{pro}$
goldhill	60.1	30.34	-4.24	55.90	30.639
baboon	60.1	26.72	-40.2	19.8	33.973
barbara	60.1	30.88	10.8	71.0	29.947
lenna	60.1	32.62	32.3	92.5	30.717
aerial	60.1	28.34	-20.4	39.6	30.687
airfield	60.1	27.05	-36.3	23.8	32.521
frisco	60.1	34.68	57.6	117.	31.155
Diego	60.1	26.44	-43.8	16.3	35.210
mrt_prepare	60.1	32.89	35.6	95.8	24.510
Variance		9.1183			9.0517

Complex texture image test experiment

By comparing the data, it can be seen that large errors of the designed two-step method often appear in images with complex structure images (e.g., Baboon, Airfield, Diego). To analyze these effects more in detail, 30 texture images [13] have been chosen for testing. The image set and their titles are shown in Fig. 7. There are two reasons for choosing these images. First, these images are not in the image library from which the average rate-distortion curve was obtained earlier. The testing of these images can more objectively reflect the real application of the two-step method. Secondly, these images contain texture structures with different degrees of complexity.

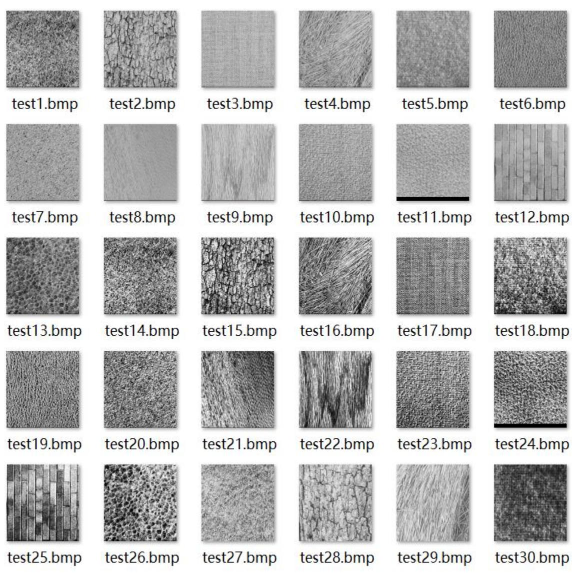

Fig7. Texture test image set

The test results can to some extent reflect the impact of the complexity of the texture structure of the image on the accuracy that can be achieved by two-step compression. Test statistics is shown in Table 5. Alongside with the data for the metric PSNR is paid the main attention in this paper, visual quality metrics are considered.

Here M_{des} is the desired value of the considered visual quality metric, M_{pro} is the provided value of the considered visual quality metric, VAR_{fis} is the variance of visual quality metric for thirty test images obtained after the first-stage compression, VAR_{sec} is variance of visual quality metric obtained after the second (correcting) step of compression, $MAX_{\Delta final}$ is Maximum error between M_{des} and the provided values M_{pro}. From the statistical results, it can be seen that for the metrics PSNR-HVS and PSNR-HVS-M the two-step method works well enough, and the variance after the two steps is considerably, by approximately one order, smaller than the variance of the first step. Meanwhile, the error is also well controlled, which is better reflected for PSNR-HVS. For the PSNR metric, more problems are revealed. When the desired value is 40 dB, the two-step method still works. When the desired value is 35 dB and, especially 30 dB, abnormal situations occur. The experimental data when $PSNR_{des}$ = 30 dB are shown in detail below (Table 6).

Table 5

Statistics of nine test images

Visual quality Evaluation Metric	M_{des}	VAR_{fis}	VAR_{sec}	$MAX\Delta_{final}$
PSNR	40	0.2852	0.280	1.5763
PSNR	35	1.5048	32.3906	29.3603
PSNR	30	3.692	N/A	
PSNR-HVS	40	0.0314	0.0011	0.0892
PSNR-HVS	35	0.1862	0.0097	0.3517
PSNR-HVS	30	0.6208	0.1528	1.3796
PSNR-HVS-M	40	5.6079	0.194	1.3653
PSNR-HVS-M	35	4.6928	0.4413	1.5423
PSNR-HVS-M	30	1.8633	0.2485	1.0542

As one can see, $PSNR_{init}$ varies in wide limits starting from approximately 24dB and completing by approximately 33dB. This means that even if an image subject to lossy compression is fully textural (recall that the test images are taken from the database of texture images [13]) there is a probability that some of them can be compressed well and ΔQS can be positive. However, for most textural images, the situation is the opposite. For the most complex structure (problematic) images, the recommended value of the recommended QS occurs to be negative (marked by red), and this causes the procedure to stop running because QS should be positive by definition. Another observation to note is that for data (marked by red blue) the operation of the two-step procedure is also improper since the errors of providing $PSNR_{des}$ are generally very large.

This means that some actions have to be undertaken to make the two-step procedure operation better. It is possible to observe from data in Table 6 that when |ΔQS| is greater than $0.5QS_{init}$, the correction starts losing sense. To our opinion, there are the following reasons behind this. Recall that the basis of the two-step method is that, within a certain area, the average rate-distortion curve and the rate-distortion curves of particular images are approximately parallel and linear approximations can be used to describe the curves locally. It can be seen from the graph in the second Section that when QS<30, this effect gradually disappears.

Table 6

Statistics and parameters of providing $PSNR_{des}$=30 dB for texture images

Test image	QS_{init}	$PSNR_{ini}$	ΔQS	QS_{rec}	$PSNR_{pro}$
test1	60.148	25.705	-52.881	7.267	41.734
test2	60.148	26.705	-40.571	19.577	33.955
test3	60.148	26.48	-43.339	16.809	34.965
test4	60.148	26.737	-40.175	19.973	33.948
test5	60.148	26.454	-43.659	16.489	35.042
test6	60.148	25.443	-56.107	4.041	46.525
test7	60.148	26.836	-38.956	21.192	33.384
test8	60.148	32.835	34.905	95.053	29.663
test9	60.148	30.938	11.549	71.697	30.064
test10	60.148	28.176	-22.458	37.691	30.757
test11	60.148	28.088	-23.541	36.607	30.581
test12	60.148	27.53	-30.411	29.737	31.182
test13	60.148	27.297	-33.280	26.868	32.071
test14	60.148	25.099	-60.342	-0.194	-
test15	60.148	25.211	-58.963	1.185	56.455
test16	60.148	25.285	-58.052	2.096	51.6
test17	60.148	24.68	-65.501	-5.353	-
test18	60.148	24.243	-70.882	-10.733	-
test19	60.148	24.398	-68.973	-8.825	-
test20	60.148	24.458	-68.234	-8.086	-
test21	60.148	25.231	-58.717	1.431	54.525
test22	60.148	26.108	-47.919	12.229	37.446
test23	60.148	25.561	-54.654	5.494	44.061
test24	60.148	24.709	-65.144	-4.996	-
test25	60.148	24.548	-67.126	-6.978	-
test26	60.148	25.464	-55.848	4.300	46.07
test27	60.148	26.863	-38.623	21.525	33.677
test28	60.148	27.616	-29.352	30.796	31.571
test29	60.148	29.249	-9.246	50.902	30.223
test30	60.148	25.938	-50.012	10.136	38.92

This is why the data marked in blue in Table 6 have large errors. If the error of the M_{init} at the first step continues to increase, the corrected QS will be negative. Besides, the correction is calculated based on the corresponding derivative M' at M_{init}. When the error of the M_{init} value is large, it is not consistent with the actual situation to calculate with the M' corresponding to M_{init}.

This shows that the two-step method has a certain range of applications. If it exceeds this range, its use needs to be restricted. We propose to analyze ΔQS. If $|\Delta QS|>0.5QS_{init}$, then set:

$$\Delta QS = 0.5 QS_{init}. \quad (3)$$

The data for the modified algorithm that employs (2) and (3) are as follows (Table 7).

Table 7
Statistics and parameters of providing $PSNR_{des}$=30 dB with constraint

Test image	QS_{init}	$PSNR_{init}$	ΔQS	QS_{rec}	$PSNR_{prov}$
test1	60.148	25.705	-52.881	30.074	30.486
test2	60.148	26.705	-40.571	30.074	30.926
test3	60.148	26.48	-43.339	30.074	30.717
test4	60.148	26.737	-40.175	30.074	31.065
test5	60.148	26.454	-43.659	30.074	30.594
test6	60.148	25.443	-56.107	30.074	30.146
test7	60.148	26.836	-38.956	30.074	30.931
test8	60.148	32.835	34.905	95.053	29.663
test9	60.148	30.938	11.549	71.697	30.064
test10	60.148	28.176	-22.458	37.691	30.757
test11	60.148	28.088	-23.541	36.607	30.581
test12	60.148	27.53	-30.411	29.737	31.182
test13	60.148	27.297	-33.280	30.074	31.320
test14	60.148	25.099	-60.342	30.074	30.153
test15	60.148	25.211	-58.963	30.074	30.136
test16	60.148	25.285	-58.052	30.074	30.228
test17	60.148	24.68	-65.501	30.074	29.876
test18	60.148	24.243	-70.882	30.074	29.685
test19	60.148	24.398	-68.973	30.074	29.744
test20	60.148	24.458	-68.234	30.074	29.779
test21	60.148	25.231	-58.717	30.074	30.158
test22	60.148	26.108	-47.919	30.074	30.560
test23	60.148	25.561	-54.654	30.074	30.446
test24	60.148	24.709	-65.144	30.074	29.956
test25	60.148	24.548	-67.126	30.074	29.856
test26	60.148	25.464	-55.848	30.074	30.387
test27	60.148	26.863	-38.623	30.074	31.374
test28	60.148	27.616	-29.352	30.7958	31.571
test29	60.148	29.249	-9.246	50.9079	30.223
test30	60.148	25.938	-50.012	30.074	30.476
Var		3.823			0.281

The experimental data show that when the application of the standard two-step method is restricted, the modified method of obtaining QS has achieved good results.

The variance has been reduced by one order, and the maximum error does not exceed 1.58 dB.

Conclusion

The simplicity and practicality of the two-step method makes it feasible to promote the use of lossy compression. The paper analyzes the errors of PSNR providing and further improves the applicability of the method to complex texture images. The use of the two-step method in the remote sensing and medical imaging ensures high accuracy of image quality providing.

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АНАЛІЗ ДВОЕТАПНОГО ПІДХОДУ ДО СТИСНЕННЯ ТЕКСТУРНИХ ЗОБРАЖЕНЬ З БАЖАНОЮ ЯКІСТЮ

Ф. Лі, С. С. Кривенко, В. В. Лукін

Розглядається задача стиснення з втратами даних дистанційного зондування та інших типів зображень із забезпеченням бажаної якості. Якість в основному характеризується піковим співвідношенням сигнал / шум (PSNR), але також коротко вивчаються інші показники якості зображення. Потенційно, двоетапний підхід може використовуватися для виконання стиснення із забезпеченням бажаної якості досить простим способом і з зменшеним часом стиснення. Однак двоетапний підхід може зіткнутися з проблемами для метрики PSNR в умовах, коли необхідний PSNR досить малий (близько 30 дБ). Ці проблеми в основному стосуються точності забезпечення бажаної якості на другому етапі. В роботі аналізуються причини, за якими це відбувається. Для цього спочатку проаналізовано набор з дев'яти тестових зображень різної складності. Потім використання двоетапного підходу вивчається для широкого набору тестових зображень зі складною структурою текстури. Відповідні тестові експерименти проведені для декількох значень бажаного PSNR. Отримані результати показують, що двоетапний підхід має обмеження в тих випадках, коли складні текстурні зображення повинні бути стиснуті з забезпеченням відносно низьких значень бажаного PSNR. Основна причина полягає в тому, що залежність швидкості від спотворення є нелінійної, тоді як на другому етапі використовується лінійне наближення. Щоб обійти вищезгадані недоліки, пропонується просте, але ефективне рішення на основі проведеного аналізу. Показано, що завдяки запропонованій модифікації область застосування двоетапного методу стиснення з втратами стала значно ширше і охоплює значення PSNR, які зазвичай потрібні на практиці. Експерименти виконуються для типового кодера AGU основі дискретно-косинусного перетворення (DCT), але можна очікувати, що запропонований підхід може бути застосовано для інших методів стиснення зображень на основі DCT.

Ключові слова: двоступеневий підхід; стиснення з втратами; бажана точність; складне зображення; текстури

АНАЛИЗ ДВУХЭТАПНОГО ПОДХОДА ДЛЯ СЖАТИЯ ТЕКСТУРНЫХ ИЗОБРАЖЕНИЙ С ЖЕЛАЕМЫМ КАЧЕСТВОМ

Ф. Ли, С.С. Кривенко, В.В. Лукин

Рассматривается задача сжатия с потерями данных дистанционного зондирования и других типов изображений с обеспечением желаемого качества. Качество в основном характеризуется пиковым отношением сигнал / шум (PSNR), но также кратко изучаются другие показатели качества изображения. Потенциально, двухэтапный подход может использоваться для выполнения сжатия с обеспечением желаемого качества довольно простым способом и с уменьшенным временем сжатия. Однако двухэтапный подход может столкнуться с проблемами для метрики PSNR в условиях, когда требуемый PSNR довольно мал (около 30 дБ). Эти проблемы в основном касаются точности обеспечения желаемого качества на втором этапе. В статье анализируются причины, по которым это происходит. Для этого сначала анализируется набор из девяти тестовых изображений различной сложности. Затем использование двухэтапного подхода изучается для широкого набора тестовых изображений со сложной структурой текстуры. Соответствующие тестовые эксперименты проводят для нескольких значений желаемого PSNR. Полученные результаты показывают, что двухэтапный подход имеет ограничения в тех случаях, когда сложные текстурные изображения должны быть сжаты с обеспечением относительно низких значений желаемого PSNR. Основная причина заключается в том, что зависимость скорости от искажения является нелинейной, тогда как на втором этапе применяется линейное приближение. Чтобы обойти вышеупомянутые недостатки, предлагается простое, но эффективное решение на основе проведенного анализа. Показано, что благодаря предложенной модификации область применения двухэтапного метода сжатия с потерями стала значительно шире и охватывает значения PSNR, которые обычно требуются на практике. Эксперименты выполняются для типичного AGU кодера изображения на основе дискретно-косинусного преобразования (DCT), но можно ожидать, что предложенный подход применим для других методов сжатия изображений на основе DCT.

Ключевые слова: двухступенчатый подход; сжатие с потерями; желаемая точность; сложное изображение; текстуры

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