ADAPTIVE TWO-STEP METHOD FOR PROVIDING THE DESIRED VISUAL QUALITY FOR SPIHT

Lossy compression has been widely used in various applications due to its variable compression ratio. However, distortions are introduced unavoidably, and this decreases the image quality. Therefore, it is often required to control the quality of the compressed images. A two-step method has been proposed recently to provide the desired visual quality. The average rate-distortion curve was used to determine the proper parameter value that controls compression. However, its performance for the wavelet-based coder Set Partitioning in Hierarchical Trees (SPIHT) is insufficient because there are very wide limits of visual quality variation for different images for a given value of the compression control parameter (CCP). Additionally, previous work has demonstrated that the level of errors, which is the subject of our study relates to texture features of an image to be compressed, where texture presence is an inherent property of remote sensing images. In this paper, our goal is to develop an adaptive two-step method for SPIHT to improve accuracy. The following tasks were solved. First, a prediction of visual quality for a particular parameter value is conducted. The prediction scheme is based on the information extraction from a certain number of image blocks to perform a visual quality calculation of the image compressed for a given CCP value. A threshold is adopted as the complexity grouping; in this paper, images are divided into two groups: simple and complex images. Second, the results of the grouping determine the adaptive curve model adopted. Finally, a two-step compression method is applied according to this curve. The classical metric Peak signal-to-noise ratio (PSNR) is employed to evaluate the image quality. The research method is based on a validation experiment that is conducted for an image set covering different image complexity and texture features. The comparison results of four typical desired values prove that the accuracy has been generally improved, the variances of both the first and second steps have been reduced sufficiently, and the mean absolute error has also been improved. Conclusion: the improvement effects are significant, particularly in the low desired visual quality. A remote sensing image is taken as an example to analyze in detail; the quality of the decompressed images meets the user’s visual requirement, and the errors are acceptable.

Keywords: two-step approach; lossy compression; desired quality; adaptive curve model.

Introduction

Nowadays, images have become the most critical data in information recording and transmission with the development of imaging technology and the extensive use of various smart applications [1-3]. A dramatic increase in the size and volume of images is observed, which leads to the difficulty in data saving and transferring in conditions of a limited bandwidth of a communication line. Consequently, compression is the essential mean to reduce the size to save storage space and improve transmission efficiency.

In general, compression techniques can be divided into two categories, namely lossless and lossy, respectively [4, 5]. The latter is widely used since it produces higher compression ratio (CR) than the former. This is especially important for remote sensing (aerial and satellite) images collected from platforms with limited storage resources and limited transmission bandwidth, such as airborne and spaceborne [6, 7].

However, the cost is that a certain degree of distortion will be introduced alongside high CR. Severe distortion results in the decompressed images’ poor quality and affects further processing or visual perception. Therefore, like CR, image quality is also an important factor in lossy compression and should even be considered as a priority in many cases [8-10]. If the terminal is a human, noticeable distortions will be visible and affect the visual perception [1, 11]; if the decompressed images need to be processed by machine algorithms, poor quality negatively influences the object estimation accuracy or probability of correct classification [12-14]. In these conditions, it is necessary to control the distortions within a certain range.
Generally, CR increase is accompanied by image quality decrease, and vice versa; it is determined by compression control parameter (CCP), adopted coder and image features [12, 15-17]. The essential part of controlling the distortions is setting the proper CCP for a compressed image in lossy compression according to quality requirements. Concerning this task, the earlier contributions were from two aspects. The first is providing the desired quality through the iterative method. In [18], the formulation of 2D Discrete Cosine Transform (DCT) coefficient and iterative JPEG2000 encoding scheme was proposed to control the quality of a reconstructed image. The second is based on prediction of quality based on the chosen statistical parameter. In [19], a deep learning-based picture-wise just noticeable difference prediction model was proposed for lossy compression according to the perceptually lossy/lossless predictor results.

A two-step compression method has been proposed recently, which avoids the multi-iteration to improve time efficiency and correct the parameter in terms of the initial quality of the first step compression to reduce the error [20-22]. Given this, the two-step method outperforms the existing distortion control methods. Our previous works have proved that this method works well for the DCT-based coder AGU and HEVC-based coder BPG [21-23], and its adaptive version reduces the errors for the metric PSNR [24]. However, the accuracy of providing a desired quality for the Discrete Wavelet Transform (DWT)-based coder Set Partitioning in Hierarchical Trees (SPIHT) is insufficient sometimes [25] because of several reasons that will become clear after more detailed analysis.

The goal of this paper is to propose and study the adaptive two-step method for the SPIHT coder and to further improve its accuracy. It is confirmed by the validation experiment that pre-classification of image complexity helps to choose the appropriate curve model and does improve the results in terms of PSNR, which had large errors in our previous works.

The rest of this paper is organized as follows. Positive features of SPIHT are described in Section 1. The basics of the two-step method applied to SPIHT are defined in Section 2. Adaptation strategy is described in Section 3. The experiment validation is presented in Section 4. The discussion is given in Section 5. Finally, Section 6 summarizes the work and provides conclusions.

1. Peculiarities and applications of SPIHT

SPIHT [26] is known to be one of popular methods of lossy image compression. It uses wavelet decomposition of an image to be compressed and inherent similarities across the sub-bands. The most important wavelet coefficients are coded in the first order. Due to this, similarly to the later introduced standard JPEG2000, several positive features are provided. First, progressive compression can be provided. Second, a desired compression ratio can be ensured. Third, better performance compared to JPEG in terms of traditional quality metrics as mean square error (MSE) or peak signal-to-noise ratio (PSNR) is usually achieved. In addition, SPIHT is rather fast and can be freely used. These advantages can be extremely useful if the main requirements to image compression method and algorithm stem from the desire to transfer a compressed image via a band-limited communication link within a given time.

The aforementioned properties explain the wide use of SPIHT in practice. For example, SPIHT application for lossy compression of medical images in magnetoresonance and computer tomography systems is considered in the papers [27, 28]. The use of different modifications is analyzed by many researchers. In particular, the use of different wavelets is studied in [28], the authors of [29] consider the use of Burrows-Wheeler transform within the SPIHT framework in attempts to improve general performance of the SPIHT coder.

Performance of SPIHT is mostly analyzed in terms of conventional quality metrics as MSE or PSNR. Meanwhile, there is an obvious tendency to using visual quality metrics including combined ones [30]. However, even for the conventional metrics, there are certain problems for SPIHT if it is desired to provide not a given CR, but a desired quality. For a given CR or bits per pixel (BPP), quality of images compressed by SPIHT (as well as by many other compression techniques) vary in very wide limits (see data in [25], the examples will be given in Section 2). Then, by setting some fixed BPP, it is difficult to provide a desired quality for any image to be compressed and one has to carry out adaptation to image content [25]. Such an adaptation can be done in different ways where the two-step method proposed in [25] and further called as basic is one of them. This method is fast (since it is based on two compressions and one decompression) but, for certain practical situations, it is not accurate enough. Thus, below we discuss how the accuracy can be improved.

2. Review of basic two-step method on SPIHT

The basic two-step method of image compression consists of two main stages. The first one is preliminary image compression/decompression with the initial CCP determined by the average rate-distortion curve obtained
off-line (in advance). The second compression stage is conducted with the recalcu-
lated CCP referring to image quality feedback in the first step. This approach is based
on several assumptions. The first assumption is that rate-distortion curves behave similarly and particular
rate-distortion curves for all images do not differ a lot
from the aforementioned averaged rate/distortion curve
obtained in one or another way. The second assumption
is that the rate/distortion curves are monotonous functions for all images and these functions can be quite
accurately approximately linearly, i.e., using only the
first derivative where derivative values for particular
rate/distortion curves are supposed to be quite close to
that one for the average curve for the same CCP. If
these assumptions do not hold, the method can fail in
one or another way or, at least, its performance can
radically worsen and become inappropriate.

In previous works, the result of applying the two-
step method to SPIHT has occurred considerably less
optimistic than for the DCT-based coder AGU [21, 25].
In particular, the largest residual errors of providing a
desired metric value took place for simple structure
images and/or low desired quality. The reason is that
these images’ rate-distortion curves differ a lot from
the average one, which led to the inappropriate initial CCP
and erroneous estimate of derivative used in calculation
of the corrected CCP.

![Dependences of PSNR on BPP for SPIHT](image)

1. Dependences of PSNR on BPP for SPIHT

![Sample images: a) Frisco, b) Goldhill](image)

Fig. 2. Sample images: a) Frisco, b) Goldhill

A part of average rate-distortion curve is given in
Figure 1, two examples of particular rate/distortion
curves are also presented for comparison and detailed
analysis. The images are shown in Figure 2. The curve
for the test image Goldhill is very similar to the average
one; therefore, accuracy of quality provided by the
conventional two-step method for this test image is
high, the residual error is appropriate [25]. However, for
the simple structure image Frisco (that contains large
quasi-homogeneous regions), the rate/distortion curve
differs a lot from the average curve. This results in the
residual error that is the largest among the test images
considered in [25]. Therefore, the accuracy is worth
improving especially for simple structure images and
low desired PSNR. The two-step compression method
[25] requires simultaneous fast realization of both fast
discrete wavelet and cosine transforms.

3. Adaptive two-step method
on SPIHT

Aiming at the problem that the difference in image
complexity results in the mismatch of the average rate-
distortion curve, an adaptive method was proposed for
AGU [24]. Because of its effective improvement, and
thanks to the image quality prediction method proposed
recently [31], it is possible to apply an adaptive two-step
method to SPIHT.

The main idea consists in the following. We assume that it is possible to easily, reliably and quickly
pre-classify an image to be compressed and refer it to
two (or even more) classes (categories). Having average
rate/distortion curves for all classes and assuming that
particular rate/distortion curves for images of a given
class are close to the corresponding average
rate/distortion curve, it is possible to set the initial (first
step) CCP better and to use a better estimate of
derivative in the second step.

In this study, we have limited ourselves by
considering two classes. The average rate-distortion
curves were obtained from two basic image sets. In this
paper, all basic images were divided into simple and
complex groups. The grouping was based on the image
quality prediction value for a fixed CCP, bit per pixel
(BPP) in the SPIHT coder [24, 31].

Let us briefly review the previous method of
quality prediction for SPIHT. This prediction method is
based on the fixed relationship between the dependence
of the visual quality values of the coder SPIHT and
discrete cosine transform (DCT) coder AGU [31].

\[
\text{PSNR}_{\text{SPIHT}} = \text{PSNR}_{\text{AGU}} - 0.6232, \text{dB.} \quad (1)
\]

The average dependence curves of PSNR
(PSNR_{SPIHT} and PSNR_{AGU}) on CR for two coders are
similar, and the deviation is basically fixed for each CR
value. Then, the PSNR value for SPIHT can be
calculated as equation (1). The following algorithms are adopted to obtain the prediction result:

1) for a given BPP, the CR of SPIHT is determined by CR≜8/BPP [25];

2) Then this CR value is utilized to calculate the \( P_{0q} \) for AGU according to equation (2), where the \( P_{0q} \) denotes the mean probability that quantized DCT coefficients in 8×8 blocks are equal to zero [32], calculated as equation (3):

\[
CR = 0.9462 \times \exp(2.895P_{0q}) + 1.045 \times 10^{-13} \times \exp(35.52P_{0q}) ,
\]

\[
P_{0q} = \frac{\sum_{n=1}^{N} N_n}{(64N_{bl})} .
\]

3) search for the proper QS value corresponding to the \( P_{0q} \). First, set an initial value of QS, e.g., equal to 0, then gradually increase it until the percentage of DCT coefficients with absolute values smaller than QS/2 is smaller than \( P_{0q} \);

4) predict the PSNR for AGU according to the following equations

\[
D_q(n,k,l) = \frac{D(n,k,l)}{QS} , k = 0,...,7; l = 0,...,7; \quad (4)
\]

\[
\Delta D_q(n,k,l) = QS \times D_q(n,k,l) - D(n,k,l), \quad k = 0,...,7; l = 0,...,7; \quad (5)
\]

\[
MSE = \frac{1}{N} \sum_{n=1}^{N} MSE_n = \frac{1}{64N} \sum_{n=0}^{N} \sum_{k=0}^{7} \sum_{l=0}^{7} (\Delta D_q(n,k,l))^2; \quad (6)
\]

\[
PSNR = 10 \times \log_{10} \left( \frac{\text{MAX}^2}{MSE} \right) , \quad (7)
\]

where \( D(n,k,l) \) denotes a set of DCT coefficient for an \( n \)-th block, \( \Delta D_q(n,k,l) \) denotes the difference after quantification, \( \text{MAX} \) defines the image dynamic range;

5) plus the fixed average deviation on the prediction PSNR of the coder AGU as equation (1). Finally, the predicted PSNR for SPIHT is obtained.

This prediction approach described above provides an estimate value of PSNR for a given BPP using some calculation to replace the actual compression. The time consumption is about 2/3 of SPIHT compression, and the standard deviation of residual errors of providing a desired PSNR is about a few dB.

In this paper, the predicted value (7) is utilized to pre-classify an image to be compressed to two groups, simple and complex structure ones. The BPP is given as 0.5, 300 8×8 random image blocks are chosen to calculate the prediction PSNR (7). The basic image set prediction results are shown in Figure 3.

![Fig. 3 Prediction of PSNR for SPIHT (BPP=0.5)](image)

Let us set the PSNR=30 dB as the threshold (Horizontal dotted line in Fig. 3); if the prediction PSNR is larger than 30 dB, then the image is treated as the simple one (marked as a red dot). Otherwise, it belongs to the complex image set (marked as a black square).

As we can see in Fig. 3, most images belong to the class of “complex structure images”. Only 7 out of 39 test images have been classified as simple structure ones.

The average curves drawn from images of two classes are shown in Figure 4. It can be seen from analysis of these curves that the average values for simple images are considerably (by 10-15 dB) higher than for the complex ones due to image different complexity.

![Fig. 4. Grouped dependences of PSNR on BPP for SPIHT](image)

The proposed pre-classification approach is performed for each image to be compressed.
Methods and means of image processing

The considered image is automatically classified as simple or complex images; the average curve is chosen adaptively; the two-step method is implemented according to the following equations:

\[ \text{BPP}_{\text{init}} = \text{BPP}_{\text{est}} + \frac{\text{PSNR}_{\text{des}} - \text{PSNR}_{\text{ave}}}{M'} \]  \quad (8)

\[ \text{BPP}_{\text{des}} = \text{BPP}_{\text{init}} + \frac{\text{PSNR}_{\text{des}} - \text{PSNR}_{\text{init}}}{M'} \]  \quad (9)

where \( \text{BPP}_{\text{est}} \) is the left margin of the adaptively chosen average rate/distortion interval, \( \text{PSNR}_{\text{ave}} \) is the PSNR average distortion value corresponding to the BPP estimate, \( M' \) is the derivative corresponding to the BPP estimate, \( \text{PSNR}_{\text{init}} \) is the decompressed image quality in the first step, \( \text{BPP}_{\text{des}} \) is corrected by equation (2) and used at the second step of compression.

4. Validation Experiment

Below we study the proposed method for SPIHT which has several known advantages like fast execution speed and wide application in lossy compression [15, 33]. The experiment has been conducted in three stages to verify its feasibility.

First, thirty-nine gray-scale images [34, 35] were chosen as the basic image set, including nine general-purpose images and thirty texture images, some of which are shown in Figure 5. This image set was divided into two groups, and then serial experiments have been conducted for each image and a wide range of BPP values; some of the data are shown in Table 1. Finally, the average rate-distortion curves (see Figure 4) have been obtained.

![Image](image1.png)

**Fig. 5. Basic image sample:**  
a) simple images, b) complex images

Second, twenty images [34, 35] have been chosen as the test image set to conduct the validation experiment with curve models from the basic image set. These test images have been also split into two groups with the same prediction and classification strategy used in the basic image set.

Some of images are presented in Figure 6.

![Image](image2.png)

**Fig. 6. Test image sample:**  
a) simple images, b) complex images

Finally, an adaptive two-step method validation experiment has been implemented for two groups of images. Three typical values have been chosen for the metric PSNR, and the results are presented in the next section. For comparison, the results for the previous two-step method [25] for these test images have been obtained as well.

5. Discussion of the results

In this section, the experiment results are presented and comparatively analyzed. The results of the previous method are shown in Table 2, and the results for the adaptive method are given in Table 3, where the experiment was conducted for simple images and complex ones separately, but the data were combined into one Table to facilitate comparison.

In our study, four typical PSNR are chosen as the desired values, 40 dB, 35 dB, 32.5 dB, and 30 dB, respectively. These values roughly correspond to three levels of visual lossless, JDN distortions, visible distortion, and clearly visible distortion [21, 36].

For statistical analysis, the variances of image quality in the first and second steps have been calculated and denoted as \( \text{VAR}_{\text{init}} \) and \( \text{VAR}_{\text{des}} \), respectively. The \( \text{MAX}_{\text{final}} \) denotes the maximum value.

![Table](table1.png)

**Table 1**  
Dependence of PSNR (in dB) on BPP for SPIHT

| Test image | BPP | 0.5 | 0.6 | …… |
|------------|-----|-----|-----|-----|
| Mrt_prepared | …… | 38.211 | 38.742 | …… |
| Test8 | …… | 36.317 | 37.323 | …… |
| Lenna | …… | 37.235 | 38.039 | …… |
| Test9 | …… | 31.013 | 32.346 | …… |
| Baboon | …… | 25.628 | 26.497 | …… |
| Test1 | …… | 20.881 | 21.584 | …… |
| Diego | …… | 26.632 | 27.271 | …… |
| Test15 | …… | 20.373 | 21.088 | …… |
of errors for each group, and the MAE denotes the Mean Absolute Error for each group data.

From these data comparisons, it is proved that the adaptive scheme improves the overall accuracy of the two-step method for SPIHT lossy compression. First, the variances in the first step compression have been reduced sufficiently with the better initial CCP; second, the residual errors of visual quality providing are smaller and more convergent due to the adaptive selection of the average rate-distortion curve, which is more significant at a low desired quality (30 dB).

For a detailed analysis of the adaptive method on remote sensing images [37], one example is shown in Figures 7 and 8. The example image was compressed for the desired quality equal to 40 dB, 35 dB, and 30 dB, the original image and decompressed image with small CR are presented in Figure 7, a and 7, b, respectively. The image in Figure 6, b has an excellent

### Table 2

| PSNR<sub>des</sub>(dB) | VAR<sub>fir</sub> | VAR<sub>sec</sub> | MAXΔ<sub>final</sub> | MAE  |
|------------------------|------------------|------------------|---------------------|------|
| 40                     | 37.6386          | 1.9183           | 5.9907              | 0.5049 |
| 35                     | 41.831           | 5.4447           | 5.5956              | 1.5911 |
| 32.5                   | 45.0757          | 8.0088           | 6.4782              | 1.9306 |
| 30                     | 48.7648          | 13.5432          | 7.9147              | 2.5726 |

### Table 3

| PSNR<sub>des</sub>(dB) | VAR<sub>fir</sub> | VAR<sub>sec</sub> | MAXΔ<sub>final</sub> | MAE  |
|------------------------|------------------|------------------|---------------------|------|
| 40                     | 22.2946          | 2.4362           | 5.81                | 0.8618 |
| 35                     | 24.4809          | 5.2552           | 4.7989              | 1.7228 |
| 32.5                   | 19.9957          | 1.6254           | 4.76                | 0.6347 |
| 30                     | 32.9900          | 2.0219           | 5.378               | 0.7799 |

Fig. 7. Remote sensing image example: a) original image, b) PSNR<sub>p<sub>ps</sub>= 40.708, CR = 4.086

Fig. 8. Remote sensing image example: a) PSNR<sub>p<sub>ps</sub>= 33.944, CR = 7.160, b) PSNR<sub>p<sub>ps</sub>= 27.098, CR = 19.112
quality, which is indistinguishable from the original image. The image in Figure 8, a has a good quality, and the distortion is not easy to notice; the image in Figure 8, b has relatively bad quality, but it allows to understand the content of the image in spite of distortions that are mainly concentrated in texture/detail areas; meanwhile the high compression ratio (CR) is achieved. The example also shows that the largest residual error is observed for PSNR$_{res} = 30$ dB.

It is demonstrated that the proposed adaptive method for two-step compression is able to provide the desired quality for SPIHT coder. The user can set a proper desired value according to requirements for a given application, and achieve the highest CR.

6. Conclusions

In this study, we have presented an adaptive two-step method of providing the desired quality for the SPIHT coder to improve the accuracy. The proposed scheme employs different average rate-distortion curves for an image to be compressed depending on its complexity which is characterized by the prediction of the decompressed image corresponding to a fixed CCP. Experimental results have demonstrated the effectiveness of the proposed scheme especially if the desired quality is quite low according to PSNR. The pre-classification algorithm is fast and helps to improve the two-step method for the SPIHT coder.

Applicability of the proposed approach is demonstrated for one remote sensing image. Lossy compression of panchromatic remote sensing data is one possible area where the adaptive two-stage method can be useful taking into account wide limits of complexity variations of such images. In addition, image complexity can be analyzed for Y component of color and multispectral remote sensing data for compression of which SPIHT and its multichannel modifications are employed. Besides, it is expected that the adaptive version can be exploited for medical image compression especially when visually lossless compression is needed.

In the future, we expect that a simpler and faster image complexity algorithm can be found for the two-step method, and more refined adaptive curves will be employed to further improve the accuracy.

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АДАПТИВНИЙ ДВОЕТАПНИЙ МЕТОД ЗАБЕЗПЕЧЕННЯ БАЖАНОЇ ВІЗУАЛЬНОЇ ЯКОСТІ ДЛЯ SPIHT

Ф. Лі

Стиснення з втратами широко використовується в різних додатках завдяки змінному коефіцієнту стиснення. Однак неминуче вносяться спотворення, і це знижує якість зображення. Таким чином, часто потребується уточнення стиснення для забезпечення бажаної візуальної якості. Основним параметром стиснення використання для визначення правильного значення параметра, що контрольує стиснення. Однак ефективність підходу для вейвлетного кодера Set Partitioning in Hierarchical Trees (SPIHT) є недостатньою, оскільки існують дуже широкі межі варіації візуальної якості для різних зображень.

Адаптивний двоетапний метод забезпечення бажаної візуальної якості для SPIHT

Ф. Лі

Стиснення з втратами широко використовується в різних додатках завдяки змінному коефіцієнту стиснення. Однак неминуче вносяться спотворення, і це знижує якість зображення. Таким чином, часто потребується уточнення стиснення для забезпечення бажаної візуальної якості. Основним параметром стиснення використання для визначення правильного значення параметра, що контролює стиснення. Однак ефективність підходу для вейвлетного кодера Set Partitioning in Hierarchical Trees (SPIHT) є недостатньою, оскільки існують дуже широкі межі варіації візуальної якості для різних зображень. Крім того, попередня робота продемонструвала, що рівень помилок, що є предметом нашого
АДАПТИВНЫЙ ДВУЭТАПНЫЙ МЕТОД ОБЕСПЕЧЕНИЯ ЖЕЛАЕМОГО ВИЗУАЛЬНОГО КАЧЕСТВА ДЛЯ SPIHT

Ф. Ли

Сжатие с потерями широко используется в разных приложениях благодаря изменяющемуся коэффициенту сжатия. Однако неизбежно вносятся искажения, и это снижает качество изображения. Таким образом, часто следует контролировать качество сжатых изображений. Недавно был предложен двухэтапный метод для обеспечения желаемого визуального качества. Средняя кривая коэффициент сжатия/искажения использована для определения правильного значения параметра, контролирующего сжатие. Однако эффективность подхода для вейвлетного кодера Set Partitioning in Hierarchical Trees (SPIHT) недостаточна, поскольку существуют очень широкие пределы вариации визуального качества для различных изображений для фиксированного значения параметра, управляющего сжатием. Кроме того, предыдущая работа продемонстрировала, что уровень ошибок, являющийся предметом нашего исследования, связан с текстурными особенностями изображения, которое нужно сжать, где наличие текстуры является неотъемлемым свойством изображений дистанционного зондирования. В данной работе нашей целью является разработать адаптивный двухэтапный способ для повышения точности для SPIHT. Реализуются следующие задачи. Во-первых, производится прогнозирование визуального качества для определенного значения параметра. Схема прогнозирования базируется на извлечении информации из определенного количества блоков для оценки визуального качества для сжимаемого изображения с заданным значением параметра, который контролирует сжатие. Для групировки по сложности используется порог; изображение делится на две группы: простые и сложные. Во-вторых, по результату групировки выбирается модельная кривая. Наконец, согласно этой кривой, применяется двухэтапное сжатие. Для оценки качества изображения используется классическая метрика – пиково отношение сигнал/шум (PSNR). Метод исследования базируется на эксперименте для набора изображений, охватывающих разную сложность и особенности текстуры, проводится проверочный эксперимент. Результаты сравнения для четырех типичных желаемых значений показывают, что точность в целом повышена, существенно улучшена. Средняя абсолютная ошибка также уменьшилась. Вывод: эффект улучшения значительный, особенно при низком желаемом визуальном качестве. Изображение дистанционного зондирования берется в качестве примера для детального анализа; качество распакованных изображений соответствует визуальным требованиям пользователей и ошибки допустимы.

Ключевые слова: двухэтапный подход; сжатие с потерями; желаемое качество; модель адаптивной кривой.

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