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TWO-STEP PROVIDING OF DESIRED QUALITY IN LOSSY IMAGE COMPRESSION BY SPIHT

Image information technology has become an important perception technology considering the task of providing lossy image compression with the desired quality using certain encoders Recent researches have shown that the use of a two-step method can perform the compression in a very simple manner and with reduced compression time under the premise of providing a desired visual quality accuracy. However, different encoders have different compression algorithms. These issues involve providing the accuracy of the desired quality. This paper considers the application of the two-step method in an encoder based on a discrete wavelet transform (DWT). In the experiment, bits per pixel (BPP) is used as the control parameter to vary and predict the compressed image quality, and three visual quality evaluation metrics (PSNR, PSNR-HVS, PSNR-HVS-M) are analyzed. In special cases, the two-step method is allowed to be modified. This modification relates to the cases when images subject to lossy compression are either too simple or too complex and linear approximation of dependences is no more valid. Experimental data prove that, compared with the single-step method, after performing the two-step compression method, the mean square error of differences between desired and provided values drops by an order of magnitude. For PSNR-HVS-M, the error of the two-step method does not exceed 3.6 dB. The experiment has been conducted for Set Partitioning in Hierarchical Trees (SPIHT), a typical image encoder based on DWT, but it can be expected that the proposed method applies to other DWT-based image compression techniques. The results show that the application range of the two-step lossy compression method has been expanded. It is not only suitable for encoders based on discrete cosine transform (DCT) but also works well for DWT-based encoders.

***Keywords**：two-step method; image lossy compression; DWT; SPIHT; desired quality*

Introduction

In recent years, with the development of information communication and digital imaging technologies, images have become the main means of information recording. Sensor resolution and size of images have increased dramatically, especially in such fields as Internet of Things, remote sensing, and intelligent medical treatment [1 - 4]. The ultimate goal of imaging and image processing can be different including object or target detection [5, 6], classification [2, 7], remote browsing [8], human perception [9, 10], etc. In any case, image transmission and/or storage are required. The increase of image size increases time taken by data transmission for a given channel bandwidth and requires more space for image storage. Because of this, image compression technology is developing synchronously providing opportunities to reduce the image size sufficiently [8, 9].

However, it should be noted that the transmission and storage of images is only a process, not the ultimate goal. Similarly, compression is the tool for image size reduction. Meanwhile, for lossy compression, one needs to ensure that a compressed image can still be used to reach the ultimate goal, i.e., image distortion caused by compression do not have a critical effect.

In opposite to lossless compression, lossy compression can easily achieve rather high values of compression ratio (CR), but it also introduces distortions; some lossy compression should be evaluated in terms of image quality to ensure that it provides no effect (or an appropriately small negative effect) on execution of a final goal. Due to this, research on image quality assessment (IQA) with application to lossy compression has also become a hot field [11 - 13].

Analysis of existing literature [14 - 16] shows that there are several important issues in lossy compression. There are numerous compression techniques designed so far [16 - 18] including standards and special purpose techniques. They have different advantages and drawbacks. Some are characterized by good visual quality of compressed images [17, 19], others are very fast or ensure high quality for compression of region of interest [20]. Many wavelet-based compression techniques as JPEG2000 or SPIHT [21 - 23] are able to easily provide a desired CR which can be very important in some applications. However, quality of an image compressed with a given CR can vary in very wide limits depending on image complexity [24, 25]. Then, a question arises how to provide a desired quality for images compressed by such coders with ensuring high accuracy of image quality providing. One more important aspect is that, in many modern applications, just visual quality of compressed images is crucial.

Note that the task of providing a desired quality according to a chosen quality metric can be potentially solved by iterative procedures that employ multiple compression/decompression, quality estimation, and coder parameter changing towards a final value [17]. This procedure is usually time consuming which can be a serious drawback. To partly solve the problem, a two-step procedure has been recently proposed for compression techniques based on discrete cosine transform (DCT) [26, 27]. But these methods use quantization step or scaling factor to control compression characteristics (CR and quality). Meanwhile, performance of SPIHT is controlled by BPP (bits per pixel) connected with CR. So, our goal is to analyze whether or not the two-step principle is applicable for SPIHT. Another goal is to understand what are peculiarities of providing a desired peak signal-to-noise ratio (PSNR) and other quality metrics in this case.

This paper is organized as follows. Section II analyzes the state-of-the-art of the research. In Section III, the encoder and visual quality metrics used in this study are introduced. The fourth Section mainly involves the use of the two-step method in SPIHT. Section V uses a two-step method to evaluate the image quality employing visual quality metrics. Section VI analyzes the experimental results in detail. Then, we give conclusions and suggestions.

Review of research status

Many researchers have conducted studies on improving the compression ratio of lossy compression [12, 13], while some researchers have performed analysis on evaluation of image quality in lossy compression [14 - 16], trying to strike a balance between compression ratio and introduced distortions. If the compression process can be performed with providing a desired image quality with appropriate accuracy, then a user can control the error when performing post-image recognition or classification tasks, otherwise the error will be cumulatively transmitted or even amplified, affecting the final task execution.

There are two main approaches to provide a desired image quality according to a used quality metric. One approach is based on prediction. The existing prediction method is to pre-compress a part of the considered image to obtain a trend prediction, thereby providing parameters for the compression of the complete image. This method is relatively simple and fast, but it is related to the selected area and the complexity of the image, and can only provide a limited accuracy. The cost of improving accuracy is to select the Salient area through the detection algorithm, or to predict by a mixture of micro and macro algorithms. Undoubtedly, these need to sacrifice compression efficiency [18-20]. Another method is to use an iterative method that presumes multiple compression / decompression, and gradually approaches the expected value of image quality. This method can get better accuracy, but the number of iterations is uncertain, and sometimes it is very large, which reduces the time efficiency of compression [17, 28].

The recently proposed two-step compression method performs this work in a novel way [26, 27]. The method first presets the parameters through the average distortion curve, and then adjusts the parameters after the first step of compression to ensure better accuracy. In the previous research work, the method has been tested and verified on the encoder based on DCT, and the results show that this method can take into account the compression efficiency and accuracy. However, the applicability of this method to encoders based on DWT such as JPEG2000 and SPIHT is uncertain and has not been studied yet. In this paper, related experiments are carried out for the encoder SPIHT which is based on wavelet transform, so as to obtain a general feasibility analysis of the method.

SPIHT-based encoder and image quality evaluation metrics

The commonly used method in lossy compression is space transfer [17 - 24] - map the spatial domain image to another space (transform domain), generate a set of transform coefficients, and then quantize, encode and transmit these coefficients. This process results in loss of information, and, at the same time, it obtains zero data for easy storage, which improves the compression ratio. The commonly used transforms are DCT and DWT. DCT is adopted in such encoders as JPEG and AGU [29, 30], while discrete wavelet transform is adopted in JPEG2000 and SPIHT [8, 21 - 24]. The wavelet transform has the localization characteristics in both time and frequency domains and its multi-resolution characteristics can be combined with the human visual characteristics [31]. Considering wide application of DWT-based encoders in lossy compression, this paper chooses SPIHT encoder for detailed experiments.

Set Partitioning in Hierarchical Trees (SPIHT) is improved on the basis of embedded zero-tree wavelet

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(EZW) [32], which mainly uses the self-similarity of wavelet coefficients of the original signal at various scales to preferentially transmit wavelet coefficients with larger absolute values. Unlike the zero tree, SPIHT uses a splitting method (spatial direction tree), and the algorithm encoder and decoder use the same diversity arrangement rules. So, SPIHT has higher compression efficiency and faster execution speed.

There are three popular metrics for visual quality assessment, namely PSNR, PSNR-HVS and PSNR-HVS-M employed in this paper. PSNR is the most common and widely used objective measure of image quality, but if the end user is a human, the results characterized by this metric can be not adequate with respect to human perception. PSNR-HVS and PSNR-HVS-M [33] are visual quality metrics that take into account peculiarities of human visual system (HVS) [34] (for all these metrics, the larger values correspond to better quality). The assessment results can match well with human perception. Considering possibly different purposes of image compression, we have tested all these three visual quality metrics.

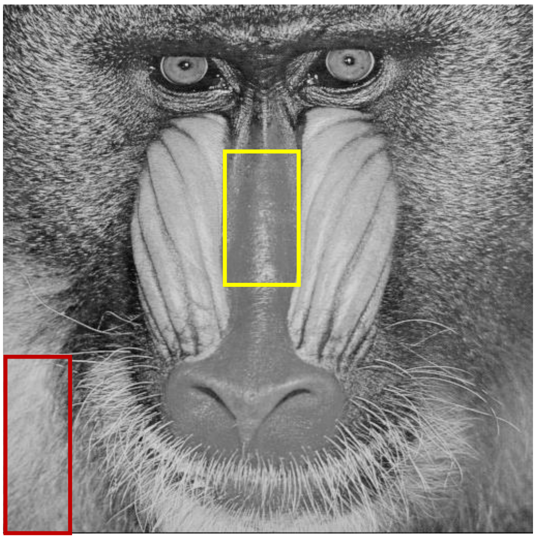
For different images, the same compression ratio (or control parameter BPP) may correspond to different visual quality, so the image quality after decompression cannot be directly determined by BPP. Let us demonstrate this using two images - Baboon and Frisco - as examples. The Baboon image has high complexity and obvious texture characteristics, while the Frisco image has low complexity and not obvious texture characteristics.

Both images are set with BPP=0.5 and the corresponding CR=16. Although the compression ratio is the same, the levels of distortions introduced to these images are different. In Fig. 1, the distortions are obvious; they are well seen in places marked by red and yellow frames. On the contrary, in Fig. 2, the compressed image is practically the same as the original image. Visual quality metric values for these two compressed images also reflect the same difference. In particular, PSNR-HVS-M for Baboon compressed image equals to 26.69 dB whilst PSNR-HVS-M for Frisco equals 42.52 dB (recall that it is considered that PSNR-HVS-M values larger than 40…42 dB correspond to invisibility of distortions).

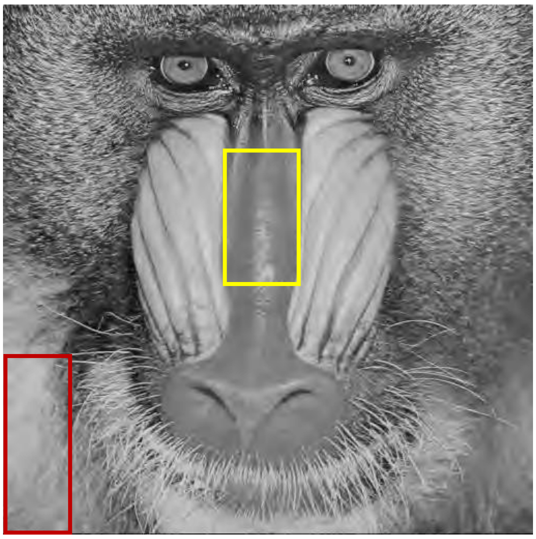
This example shows that providing a desired visual quality is not an easy task because quality of compressed image is related to its complexity and texture characteristics.

Two-step approach for SPIHT

The two-step method is a novel method recently proposed to provide a desired visual quality. The basic step is initial prediction of visual quality and parameter setting using average distortion curve. The average distortion curve reflects general relationship between visual quality and control parameters.



a



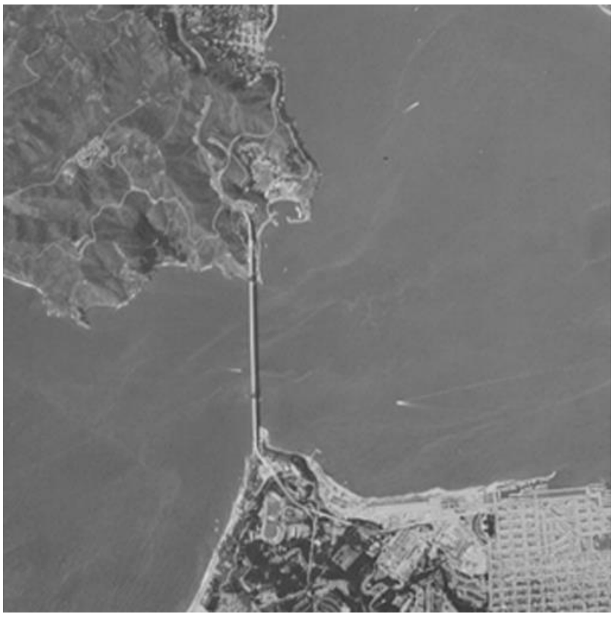
b

Fig. 1. Comparison of the original image and compressed image of Baboon: original image (a), CR=16, PSNR=25.63 dB, PSNR-HVS-M=26.69 dB (b)

In order to understand the dependence of image quality and compression ratio on control parameters, Goldhill image was used as an example for testing. The experimental results are shown in Fig. 3.

For the SPIHT encoder, BPP is used as the control parameter. As it can be seen in Fig. 1, as BPP increases, the compression ratio decreases, and the image quality improves. CR and BPP are strictly dependent where, for 8-bit representation of grayscale images, CR≈8/BPP and, vice versa, BPP≈8/CR. Thus, knowing a desired CR, one calculates BPP and SPIHT provides BPP slightly less than 8/CR. Dependences of quality metrics on BPP are monotonously increasing (or nondecreasing) but, due to specific properties of SPIHT, are not smooth.

a



b

Fig. 2. Comparison of the original image and compressed image of Frisco: original image (a), CR=16, PSNR=42.69 dB, PSNR-HVS-M=42.52 dB (b)

To provide a desired image quality through the two-step method, the average distortion curve needs to be obtained first. In this paper, nine images are used as the image library, so as to obtain the average distortion curve of a small sample. The graphs for three visual quality metrics are shown in Fig. 3, Fig. 4, and Fig. 5. Among the image library, there are four standard images (Lenna, Barbara, Baboon, and Goldhill), four remote sensing images, and one medical image, which represent a variety of images that can be subject to lossy compression. In particular, there are highly textural images Baboon and Diego whilst the test images Frisco and MRT_preparted are quite simple.

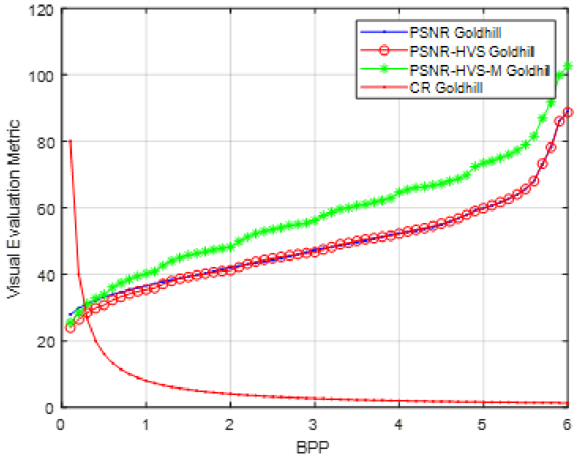


Fig. 3. Dependences of image quality and compression ratio on control parameter

In Fig.4, the distortion curve of the PSNR of each image is relatively smooth. For the same BPP value, different image values differ greatly (up to 23 dB). The simple image Frisco's curve is at the top, and it has the highest PSNR value under any BPP. The curves for Baboon and Diego that are complex structure images are at the bottom, which means that the distortions are the largest under the same CR (BPP). However, the overall change trend is consistent. The average distortion curve obtained from these nine images is locally "approximately parallel" to other curves.

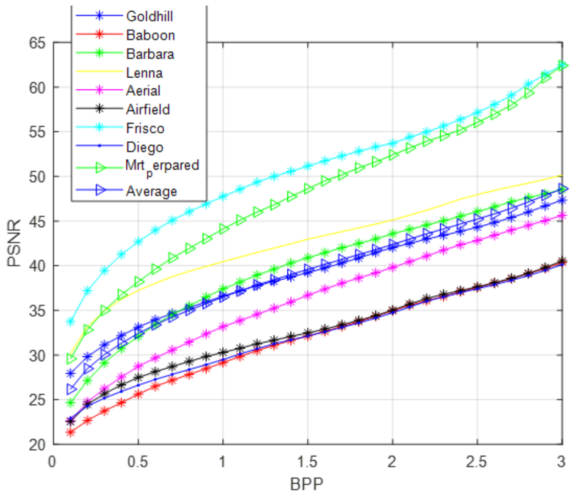


Fig. 4. Particular and average distortion curves for PSNR

In Figures 5 and 6, one can observe that, for the same BPP, values of PSNR-HVS and PSNR-HVS-M are also sufficiently different. However, for PSNR-

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HVS-M this difference is smaller than for PSNR, Complex structure images (such as Baboon) have the worst visual quality, and correspondingly, simple structure images (such as Frisco) have the best visual quality. The average distortion curves are again locally approximately parallel to dependences for particular images.

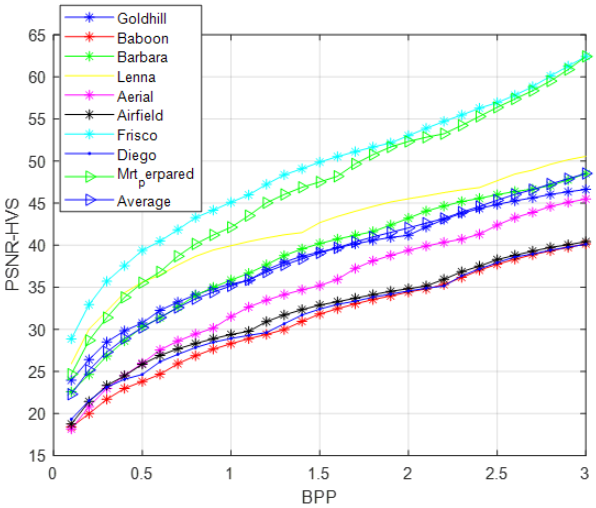

Fig. 5. Particular and average distortion curves for PSNR-HVS

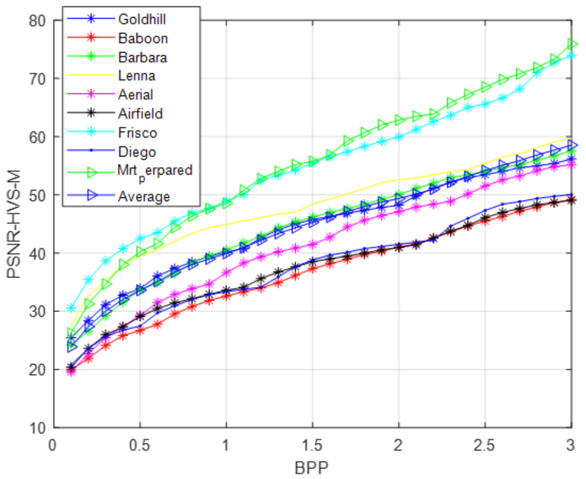

Fig.6. Particular and average distortion curves for PSNR-HVS-M

SPIHT-based experiment implementation

From the previous analysis, it can be concluded that, in SPIHT, it is feasible to perform compression prediction through the average distortion curve. In the average distortion curve, the data to be extracted are the corresponding visual quality metric values and derivatives for a series of control parameters.

Table 1

Dependence of PSNR (in dB) on BPP for SPIHT

Test image	BPP				
	0.1	…	0.7	0.8	…
Goldhill	27.949	…	34.663	35.308	…
Baboon	21.352	…	27.176	27.827	…
Barbara	24.650	…	34.549	35.493	…
Lenna	30.189	…	38.775	39.380	…
Aerial	22.631	…	30.561	31.452	…
Airfield	22.551	…	28.715	29.287	…
Frisco	33.734	…	45.091	46.052	…
Diego	22.934	…	27.834	28.379	…
MRT_prep	29.586	…	40.882	41.937	…
Average	26.175	…	34.250	35.013	…
Derivative	23.089	…	7.6301	7.5715	…

Table 1 contains a part of statistical data for the dependence of PSNR on BPP. Averaging has been done for each BPP for a set of test images, then the derivative values have been determined (they are all positive and their values decrease if BPP increases).

In the first step of compression, we propose to set the compression control parameter (PCC) according to the measured average rate/distortion curve, the argument of which in SPIHT is BPP. Let us give one example. Suppose we need to provide compression with a desired PSNR ($PSNR_{des}$) equal to 35 dB for the test image Baboon. According to the average rate/distortion statistics (see the row "Average" in Table I), the value of BPP should be between 0.7 and 0.8. Then, using linear interpolation, we can calculate initial BPP value by the following formula:

$$BPP_{init} = BPP_{est} + \frac{PSNR_{des} - PSNR_{ave}}{M'}, \quad (1)$$

where BPP_{est} is the left margin of the interval of the average rate/distortion curve (equal to 0.7 in the considered example), $PSNR_{ave}$ is the PSNR average distortion value corresponding to the BPP estimate. M' is the derivative corresponding to the BPP estimate. Using data in Table I, it can be calculated that the initial value of BPP is equal to 0.798.

After the initial value of BPP is obtained, the image Baboon is compressed at the first step and then decompressed to obtain the visual quality value corresponding to a considered image. Let us denote this value as $PSNR_{init}$. For the image Baboon, it equals to 27.815 dB. As one can see, this value is quite far from the desired value of visual quality metric (35 dB). Recalling the analysis in the third section, the Baboon image has high complexity and strong texture characteristics, which can result in poor visual quality. Of course, the accuracy of this value (difference between $PSNR_{init}$ and $PSNR_{des}$) is unsatisfactory and actions to improve the accuracy of providing $PSNR_{des}$ are needed.

In the second step of the compression procedure, a BPP corrected value for this image should be calculated using the $PSNR_{init}$ value obtained at the first step to improve accuracy. We propose to do this as follows:

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

The corrected (desired) BPP value is used at the second step of compression. The provided $PSNR_{prov}$ equals to 33.414 dB and is closer to the desired value than the $PSNR_{init}$ (27.815 dB) obtained at the first step. From this example, a specific implementation of the two-step method is shown. It is seen that after the second step of compression, the provided value $PSNR_{prov}$ is closer to the desired value PSNRdes than the initial value $PSNR_{init}$. But can the two-step method also provide precision control for the compression of other images? Further experiments and statistical data are necessary.

Analysis of compression accuracy

After the average distortion curves based on the three visual evaluation metrics are obtained separately, the image can be compressed by a two-step compression method. Taking the desired value of PNSR-HVS-M as 40dB as an example, nine images were tested, as shown in Table 2. In this Table, we give the following data: BPP_{init} calculated according to (1) and PSNR-HVS-M_{init} calculated after compression with BPP_{init} and decompression, ΔBPP calculated as $\frac{PSNR_{des} - PSNR_{init}}{M'}$ in (2), BPP_{des} calculated according to (2), PSNR-HVS-M_{prov} obtained after the second step of image compression using BPP_{des}; in the lowest line we present variance (Var) for PSNR-HVS-M_{init} and PSNR-HVS-M_{prov}, respectively.

Before starting to analyze these data in detail, let us recall the following. There are several reasons why the proposed two-step procedure can lead to residual errors in providing a desired value of a used metric. First of all, linear interpolation is used in (2) and it is valid only in a certain (not too large) neighborhood of BPP_{init} and under condition that an approximated function behaves linearly (absolute values of the second and higher derivatives are close to zero). Clearly, this is not guaranteed in our case. Secondly, linear approximation (2) exploits M' obtained for average curve as derivative estimate for all particular dependences. But this is also the idealization.

Table 2

Statistics and paramters of providing PSNR-HVS-M_{des}=40dB

Test image	BPP_{init}	PSNR-HVS-M_{init}	ΔBPP	BPP_{des}	PSNR-HVS-M_{prov}
Goldhill	1.007	40.215	-0.021	0.986	40.031
Baboon	1.007	32.688	0.721	1.729	39.186
Barbara	1.007	40.616	-0.061	0.947	39.912
Lenna	1.007	44.934	-0.487	0.521	39.762
Aerial	1.007	36.721	0.323	1.331	40.455
Airfield	1.007	33.631	0.628	1.636	39.168
Frisco	1.007	48.944	-0.882	0.504	42.565
Diego	1.007	33.388	0.652	1.660	39.962
Mrt_prepared	1.007	48.632	-0.851	0.504	40.316
Var	40.971				1.013

One can see in Table 2 that |ΔBPP| obtained for Frisco and MRT_prepared images after the first compression step is quite large - it exceeds half of the BPP_{init} value. The values obtained after BPP calculation using (2) are 0.125 and 0.156, respectively, and the PSNR-HVS-M values obtained after such parameter compression are 32.085dB and 29.186dB, respectively. So, accuracy of visual quality providing has not been improved after the second step of compression. This is due to the aforementioned factors. Really, when BPP is smaller, the curve changes steeper and the derivative changes more. At this time, the BPP is predicted by the derivative of the initial value point, which causes |ΔBPP| to be too large. This means that the expected improvement of providing visual quality accuracy cannot be ensured by Equation (2) in some cases. Similar situations happened for DCT-based encoders such as AGU and ADCTC [27, 35] controlled by quantization step. For SPIHT we propose to use similar correction formula for BPP_{des} – if the absolute value of ΔBPP is larger than BPP_{init} / 2 and ΔBPP is negative, then set

$$BPP_{rec} = BPP_{init}/2, \qquad (3)$$

then continue the two-step compression. Due to this modification, the improvement in accuracy of providing a desired quality is guaranteed. The experimental data proving this are given in Table II. After using the modified formula, the obtained visual quality values are 42.565 dB and 40.316 dB (closer to the desired visual quality value). Comparison of variance values shows that, after the second step, variance has decreased by about 40 times, i.e. considerable benefit is provided. Meanwhile, comparison to the data for AGU [27] shows that accuracy of providing a desired PSNR-HVS-M for

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SPIHT is worse (for AGU, variance of providing PSNR-HVS-M after two-steps is equal to 0.0108).

Let us test accuracy for the range of metric values that is the most important in practice. Three typical thresholds of 30 dB, 35 dB, and 40 dB for our visual quality metrics, PSNR, PSNR-HVS, and PSNR-HVS-M, respectively, have been obtained for nine test images of experimental data, which are summarized in Table 3.

Table 3

Statistics for test images

Quality metric	M_{des}	VAR_{fis}	VAR_{sec}	$MAX_{\Delta fin}$
PSNR	40	50.715	4.213	5.950
PSNR	35	39.577	9.598	7.673
PSNR	30	29.432	10.82	7.168
PSNR-HVS	40	45.320	2.175	3.517
PSNR-HVS	35	37.937	4.603	4.263
PSNR-HVS	30	31.349	3.599	4.369
PSNR-HVS-M	40	40.971	1.013	2.565
PSNR-HVS-M	35	32.867	2.922	3.598
PSNR-HVS-M	30	26.890	4.028	3.314

Here M_{des} is the desired value of the considered visual quality metric, VAR_{fis} is the variance of visual quality metric for nine test images obtained after the first-stage compression, VAR_{sec} is variance of visual quality metric obtained after the second (correcting) step of compression, $MAX_{\Delta fin}$ is Maximum error between M_{des} and provided value of the considered visual quality metric.

It can be seen from the data in this Table that the variance after the first compression step is large (up to 50.715dB^2), and the variance after the second (correction) step is an order of magnitude lower than VAR_{fis} (except $PSNR_{des}$ = 30 dB). The higher the desired visual quality, the smaller the error. In addition, through comparison, it can be concluded that the two-step method works better with employing the HVS-based visual quality metrics, and the maximum error does not exceed 5 dB. In the evaluation based on PSNR, the variance is improved, but the maximum error is still large, and more effective improvements are needed to reduce the error.

Conclusion

Through the experiments of two-step compression method applied in SPIHT encoder based on wavelet transform, it can be concluded that the method works well enough. For three visual quality metrics, the results have been improved sufficiently, and the variance after the second compression has dropped by about an order of magnitude. Of course, the maximum error of some data is still relatively large, especially for PSNR. In the future work, in response to this problem, it is expected to propose a better second-step correction method to improve the control accuracy and reduce errors.

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ДВОЕТАПНЕ ЗАБЕЗПЕЧЕННЯ БАЖАНОЇ ЯКОСТІ ПРИ СТИСНЕННІ ЗОБРАЖЕНЬ З ВТРАТАМИ ЗА ДОПОМОГОЮ КОДЕРА SPIHT

Ф. Лі, С. С. Кривенко, В. В. Лукін

Інформаційні технології відіграють важливу роль в обробці зображень, особливо в задачах стиснення зображень з втратами із забезпеченням необхідної якості. Нещодавні дослідження показали, що використання двоетапного методу дозволяє здійснити стиснення дуже простим способом, забезпечуючи при цьому зменшений час обробки за умови досягнення необхідного візуального якості. Однак різні кодери мають різні алгоритми стиснення. Зокрема, особливе місце займають питання забезпечення точності необхідної якості. У даній статті розглядається застосування двоетапного підходу в кодері на основі дискретного вейвлет-перетворення (DWT). В цьому експерименті кількість біт на один піксель зображення (BPP) використовуються в якості параметра управління якістю стислого зображення. Аналізуються три показники оцінки візуальної якості (PSNR, PSNR-HVS, PSNR-HVS-M), два з яких враховують особливості візуального сприйняття. В окремих випадках допускалася зміна двоетапного методу. Ця модифікація стосується випадків, коли зображення, що піддаються стисненню з втратами, є або занадто простими, або занадто складними, і лінійна апроксимація залежностей дає незадовільний результат. Експериментальні дані доводять, що в порівнянні з однокроковим методом після виконання двоетапного методу стиснення середньо-квадратична похибка від-

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мінностей між бажаними і одержуваними значеннями зменшується в кілька разів. Для метрики PSNR-HVS-M похибка двоетапного методу не перевищує 3,6 дБ. Експеримент був проведений для кодера SPIHT - стандартного кодера на основі DWT. Однак можна очікувати, що запропонований метод можна застосовувати до інших методів стиснення зображень на основі DWT. Результати показують, що область застосування двоетапного методу стиснення з втратами була розширена. Він підходить не тільки для кодерів, заснованих на дискретному косинусном перетворенні (DCT), але також добре працює для кодерів на основі DWT.

Ключові слова: двоступеневий підхід; стиснення з втратами; бажана точність; DWT; SPIHT

ДВУХЭТАПНОЕ ОБЕСПЕЧЕНИЕ ЖЕЛАЕМОГО КАЧЕСТВА ПРИ СЖАТИИ ИЗОБРАЖЕНИЙ С ПОТЕРЯМИ ПРИ ПОМОЩИ КОДЕРА SPIHT

Ф. Ли, С. С. Кривенко, В. В. Лукин

Информационные технологии играют важную роль в обработке изображений, особенно в задачах сжатия изображений с потерями и обеспечением требуемого качества. Недавние исследования показали, что использование двухэтапного метода позволяет осуществить сжатие очень простым способом, обеспечивая при этом уменьшенное время обработки при условии достижения требуемого визуального качества. Однако разные кодеры имеют разные алгоритмы сжатия. В частности, особое место занимают вопросы обеспечения точности требуемого качества. В данной статье рассматривается применение двухэтапного подхода в кодере на основе дискретного вейвлет-преобразования (DWT). В этом эксперименте количество бит на один пиксель изображения (BPP) используются в качестве параметра управления качеством сжатого изображения. Анализируются три показателя оценки визуального качества (PSNR, PSNR-HVS, PSNR-HVS-M), два из которых учитывают особенности визуального восприятия. В отдельных случаях допускалось изменение двухэтапного метода. Эта модификация относится к случаям, когда изображения, подвергаемые сжатию с потерями, являются либо слишком простыми, либо слишком сложными, и линейная аппроксимация зависимостей дает неудовлетворительный результат. Экспериментальные данные доказывают, что по сравнению с одношаговым методом после выполнения двухэтапного метода сжатия среднеквадратическая ошибка различий между желаемыми и получаемыми значениями уменьшается в несколько раз. Для метрики PSNR-HVS-M погрешность двухэтапного метода не превышает 3,6 дБ. Эксперимент был проведен для кодера SPIHT - стандартного кодера на основе DWT. Однако можно ожидать, что предложенный метод применим к другим методам сжатия изображений на основе DWT. Результаты показывают, что область применения двухэтапного метода сжатия с потерями была расширена. Он подходит не только для кодеров, основанных на дискретном косинусном преобразовании (DCT), но также хорошо работает для кодеров на основе DWT.

Ключевые слова: двухступенчатый подход; сжатие с потерями; желаемая точность; DWT; SPIHT

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