PAPER

Two-Layer Lossless Coding for High Dynamic Range Images Based on Range Compression and Adaptive Inverse Tone-Mapping

Taichi YOSHIDA^{†a)}, Nonmember, Masahiro IWAHASHI^{†b)}, Member, and Hitoshi KIYA^{††c)}, Fellow

SUMMARY In this paper, we propose a 2-layer lossless coding method for high dynamic range (HDR) images based on range compression and adaptive inverse tone-mapping. Recently, HDR images, which have a wider range of luminance than conventional low dynamic range (LDR) ones, have been frequently used in various fields. Since commonly used devices cannot yet display HDR images, 2-layer coding methods that decode not only HDR images but also their LDR versions have been proposed. We have previously proposed a state-of-the-art 2-layer lossless coding method for HDR images that unfortunately has huge HDR file size. Hence, we introduce two ideas to reduce the HDR file size to less than that of the previous method. The proposed method achieves high compression ratio and experiments show that it outperforms the previous method and other conventional methods.

key words: HDR image coding, 2-layer coding, lossless coding, arbitrary tone-mapping

1. Introduction

Recent developments in the imaging device field have resulted in high dynamic range (HDR) images, which have a wider range of luminance than conventional ones, becoming frequently used in various fields as natural, medical and astronomical images. In contrast with HDR images, conventional images are called low dynamic range (LDR) ones. Since HDR images ordinarily have more information than their LDR versions because of their wide luminance range, they may supersede LDR images in the future. Hence, HDR image formats have been proposed such as RGBE, LogLuv, and OpenEXR [1], [2].

However, commonly used devices cannot display HDR images. When an HDR image is shown on the devices, it must be changed into its LDR version. The changing technique is called a tone-mapping operation (TMO) and various methods for it have been proposed [1]–[13]. An efficient TMO method whose results have fine details and natural color requires a lot of time for the processing, and therefore it is generally undesirable at the decoder.

Hence, coding methods that decode not only HDR images but also their LDR versions, called two-layer (2-layer)

Manuscript received March 12, 2017.

Manuscript revised August 25, 2017.

[†]The authors are with the Dept. of Electrical, Electronics and Information Engineering, Nagaoka Univ. of Tech., Nagaoka-shi, 940-2137 Japan.

††The author is with the Dept. of Information and Communication Systems, Faculty of System Design, Tokyo Metropolitan Univ., Hino-shi, 191-0065 Japan.

a) E-mail: yoshida@vos.nagaokaut.ac.jp

b) E-mail: iwahashi@vos.nagaokaut.ac.jp

c) E-mail: kiya@tmu.ac.jp

DOI: 10.1587/transfun.E101.A.259

coding, have been proposed [14]–[23]. Two-layer coding methods compress an HDR image and produce two files: an LDR file and an additional file. From the LDR file, the methods decode an LDR version of the HDR image, and the HDR image is decoded from both files. The LDR image is a result of applying a pre-defined TMO method to the HDR image. Since LDR files are considerably smaller in size than additional files, LDR images can be acquired via the Internet much faster than decoded and tone-mapped HDR images.

Two-layer coding has two useful properties: image selectivity of difference dynamic range and backward compatibility. Image selectivity means that 2-layer coding can provide the two types of images mentioned above. Backward compatibility means that LDR versions can be decoded by commonly used coding methods such as Joint Photographic Experts Group (JPEG) [24], JPEG 2000 (JPEG 2k) [25], JPEG extended range (JPEG XR) [26], Portable Network Graphics (PNG) [27], and so on. It is particularly significant that LDR images are decoded by popular coding methods; this enables the decoding to be done without using additional circuits and software at the decoder.

Unfortunately, the above 2-layer coding methods are lossy, but lossless coding of HDR images is often required for application of computer graphics [1], [2]. HDR images are often stored in order to analyze their information and to modify them along given a specific artistic intent. Since it is undesirable to have HDR images degraded via coding, HDR images should be losslessly compressed and stored. Consequently, the 2-layer lossless HDR image coding is required.

To address this issue, we previously proposed a 2-layer lossless coding method for HDR images. In the paper reporting the method [28], 2-layer lossless coding means that HDR images are losslessly encoded, while LDR images are compressed by lossy coding. The encoding procedure is as follows: First, an input HDR image is changed into its LDR version by a predefined TMO and encoded by lossy coding. The result is called the LDR file. From the LDR file, the LDR image is decoded and changed into its HDR version by the inverse process of the TMO. The result is called a degraded HDR image. An integer version of the degraded HDR image is subtracted from the input one, using a technique that losslessly converts HDR images from real ones into integer ones [28]. Finally, the residual image is losslessly encoded into an additional file. Although this method achieves 2-layer lossless coding for HDR images, its additional files often have huge size.

To solve this problem, in this paper we propose a

2-layer lossless coding method for HDR images based on range compression and adaptive inverse tone-mapping, which contribute to reduce the pixel value range of residual images. The range compression narrows the pixel value range of HDR images and the adaptive inverse tonemapping approximates degraded HDR images to input ones. Consequently, the proposed method makes it possible to reduce the size of additional files, and we show that the method outperforms conventional and state-of-the-art methods through experiments. Unlike the conventional method, the proposed one can use an arbitrary TMO method, not only global but also local, because of its adaptive inverse tone-mapping, which means that it has the potential to produce perceptually efficient LDR images. Moreover, it can always utilize a state-of-the-art TMO method without loss of generality. Preliminary researches work related to this paper is shown in [29]-[31].

2. Related Work

HDR images are proposed to represent natural scenes similar to the human visual system [1], [2]. Humans simultaneously perceive luminance over four orders of magnitude when their eyes are adjusted to specific luminance. A range of captured luminance is called a dynamic range. Unfortunately, the dynamic range of conventional LDR images is less than two orders of magnitude. For capturing natural scenes similar to human perception, images whose dynamic range is more than four orders of magnitude have been proposed and called HDR images. Various coding formats for HDR images, mentioned in Sect. 1, have been proposed to encode scenes of wide dynamic range into discrete signals with the finite number of bits, and respectively have different dynamic range and quantization error ratio.

Ordinarily, TMO methods are categorized into global and local TMO [1]–[13]. Global TMO is a technique applying a uniform function to HDR images and achieves fast and low computational TMO. Local TMO uses an adaptive function for local regions of HDR images and produces fine LDR images while preserving important visual features such as edges, high contrast regions and textures. However, local TMO requires high computational cost and realizing its inverse function is extremely difficult. To realize a fast TMO while preserving important visual features, recent methods apply a multi-function of global TMO and selectively combine results into one image with fine details of images. Recently, efficient and complex methods of local TMO have been introduced, and their results are perceptually better than ones of global TMO [10]–[13].

During the last decade, a few one-layer (1-layer) methods and many 2-layer lossy methods of HDR image coding have been proposed [14]–[23], [32], [33]. One of the most famous 1-layer methods simply quantizes and encodes HDR images by JPEG 2k [32]. The method achieves better compression ratio than recent 2-layer methods, but does not have dynamic range scalability. The 2-layer coding method known as JPEG-HDR was first introduced in [14]. It uses a

JPEG coder for tone-mapped and residual images, and has two important properties: image selectivity of difference dynamic range and backward compatibility. Recently, optimizing TMO has become attractive for improving compression ratio in 2-layer coding [19], [21]–[23]. One method defines TMO as a piecewise linear function and optimizes it in l_2 norm of residual images [19]. Although the method achieves better compression ratio than JPEG-HDR, its LDR images are visually undesirable. Therefore, the state-of-theart method reported in [23] takes into account not only values of the l_2 norm but also visual quality of LDR images, and achieves valid performance for 2-layer lossy coding.

As international standards of image coding, JPEG series are widely used, and some of them can encode HDR images. JPEG 2k and XR support the 16- and 32-bit floating point representation data [25], [26]. Hence, they can encode HDR images of RGBE and OpenEXR. Since JPEG 2k and XR use the multi-resolution decomposition, we can display various visual quality of the encoded image by selecting resolution layers, which is called the image quality scalability. Based on the property, they achieve the image selectivity of 2-layer coding for HDR images, i.e., low resolution layers of HDR images are decoded as LDR images with the linear compression of bit depth. However, LDR images are blurred and degraded compared with tone-mapped HDR images due to the procedure. Therefore, to display fine LDR versions of HDR images without huge computational complexity, the 2-layer HDR image coding is required, and hence is standardized as JPEG extensions (JPEG XT) [34].

3. Review

3.1 Integer Conversion of HDR Images

Based on JPEG XR [26], the algorithm converting from floating point to integer numbers is briefly shown here. HDR image formats usually use the floating point representation of pixel values [1], [2]. However, for lossless coding, HDR images should be converted into the integer representation. To support OpenEXR and RGBE images, JPEG XR standardizes the converting from floating point to integer numbers [26]. In this paper, we use the convert algorithm and it is called the "integer conversion".

In the case of OpenEXR, pixels are straightforwardly decoded as signed integer. HDR images of OpenEXR are in the RGB color space and one pixel has 16 bits per color. The 16 bits consist of three groups: a sign bit, exponent bits, and mantissa bits, which respectively contain 1, 5, and 10 bits. If the sign bit is 0, the pixel is directly decoded as 16-bit signed integer number. When the sign bit is 1, the 2's complement is performed on 15 bits, whose former and latter bits are equal to exponent and mantissa bits, respectively, and then the pixel can also be decoded as 16-bit signed integer number. Finally, HDR images of OpenEXR are easily converted and their pixel values are integers in $[-2^{15}, 2^{15} - 1]$.

In the case of RGBE, the specified strategy is introduced. A pixel of RGBE images has 32 bits consisting of

four groups: R, G, and B mantissa and exponent bits that each contain 8 bits. An integer value of a pixel of R color is calculated from R mantissa and exponent bits as follows: If either the mantissa or the exponent is zero, the integer value is set 0. While the highest bit of the mantissa is 0 or the exponent is greater than 1, the left bit shift is performed on the mantissa and the exponent is decremented. When the terminal value of the exponent is 1, the mantissa is set as the integer value. When the terminal value is greater than 1, the left bit shift is performed on the terminal exponent seven times and the result is added to 7 least significant bits of the terminal mantissa. By applying the above strategy to each color component, consequently, integer values of RGBE images are calculated in $[0, 2^{15} - 1]$.

3.2 1-Layer Lossless Coding for HDR Images

Since recent image coding formats such as JPEG 2k, JPEG XR, and PNG can support 16 bits per color, they losslessly encode HDR images with the aforementioned integer conversion technique. The method transforms HDR images from real into integer by the integer conversion, and then resultant images are losslessly encoded into one of the above formats.

3.3 2-Layer Lossless Coding for HDR Images

We have previously proposed a 2-layer lossless coding method for HDR images [28], which we will refer to as the "basic method" in this paper. It is shown in Fig. 1, where the notation "Inv." denotes an inverse process. Its encoding procedure comprises the following four steps. First, an input HDR image is changed into its LDR version by a predefined global TMO and is encoded by utilizing a commonly used image coding method such as JPEG 2k, PNG, and so on. The result is called an LDR file. From the LDR file, a degraded HDR image is calculated by decoding and inverse processing of the TMO. The input and degraded HDR images are transformed into integer versions by the integer conversion, and the integer version of the degraded HDR image is subtracted from that of the input image. Finally, the residual image is losslessly encoded by an arbitrary coding method and the result is called an additional file. The

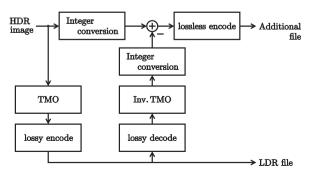


Fig. 1 Two-layer lossless coding method for HDR images, called the "basic method" in this paper.

basic method has backward compatibility and image selectivity of difference dynamic range, but its additional files are extremely large in size.

4. Proposed Method

4.1 Overview

To reduce the size of additional files, we incorporate three techniques (histogram packing, global approximation, and gradation prediction) into the basic method in Sect. 3.3. The histogram packing helps to compress the pixel value range of HDR images. The other two techniques, which together enable the adaptive inverse tone-mapping in Sect. 1, effectively reduce the difference between input and degraded HDR images. Consequently, since the techniques reduce the bit depth of residual images, the proposed method successfully reduces sizes of additional files. The details of the three techniques are explained in the following sections. Note that the proposed method apply the techniques for each color component (e.g. red, green blue).

The encoding structure of the proposed method is shown in Fig. 2. The incorporated techniques are represented in double frames. The first step is similar to that of the basic method except that an arbitrary TMO method, either global or local, can be used. An input HDR image is transformed by the integer conversion, and then its pixel value range is compressed by the histogram packing. The resultant image is called a packed HDR image. A degraded HDR image is calculated from the decoded LDR image by the global approximation referring to the packed HDR image. The gradation prediction estimates gradations of the packed HDR image from the degraded one to reduce the difference between the packed and degraded HDR images, and the result is called a predicted HDR image. Finally, a residual image is calculated from the packed and predicted HDR images and losslessly encoded. Note that the packing and approximation information is encoded and stored in the additional file as side information for decoding. The decoder side of the proposed method is shown in Fig. 3.

4.2 Histogram Packing

Histogram packing is a technique for losslessly reducing the redundancy of signal values [35], and we use it for reducing the pixel value range of HDR images. The technique replaces pixel values with nonnegative values as low as possible and removes values whose frequencies are zero. The technique is usually effective for HDR images because the histogram of HDR images is generally sparse. Consequently, since the pixel value range of HDR images is compressed, values of the difference between input and degraded HDR images are reduced.

Histogram packing losslessly replaces signal values. Here, we explain the technique in the case of signals whose values are integer. The technique outputs replaced signals

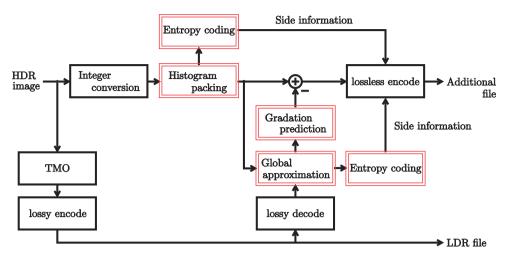


Fig. 2 Encoding structure of the proposed method.

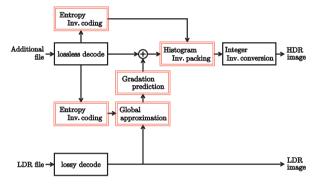


Fig. 3 Decoding structure of the proposed method.

 \hat{a} from original signals a and a lookup table t which denotes the correspondence between a and \hat{a} . The proposed method encodes t as side information. First, the technique stores values of original signals in t from lowest to highest ones without overlap, which is not the sort in ascending order, i.e., t = [2, 3, 5, 7] if a = [3, 5, 7, 2, 3]. Next, \hat{a}_m ($m = 1, 2, \dots, M$) is calculated as

$$\hat{a}_m = n - 1$$
 s.t. $a_m = t_n \ (n = 1, 2, \dots, N),$ (1)

where \hat{a}_i , a_i , and t_i are respectively *i*-th elements of \hat{a} , a, and t, and M and N respectively denote the number of signals and signal values. For reconstruction, we calculate original values from replaced values by using the lookup table. To encode the table, we recalculate the difference between adjacent values in the table, and then results are encoded by entropy coding, in this paper.

4.3 Global Approximation

Global approximation is a technique for globally mapping signal values into other values with reference signals. The technique approximates input signals to reference ones in l_2 norm. The technique consists of two steps: calculating the mapping function and applying it to input signals. The function is calculated from input and reference signals. Output

signals are produced from the function and input signals.

In this paper, the global mapping f consists of piecewise linear functions f_k ($k = 1, 2, \dots, K$) and their slopes s_k are calculated by the least squares method, where K is the number of the linear functions. First, a range of input signal values is divided into K bins with a uniform length δ . In the k-th bin, s_k is calculated from values of input signals in the k-th bin x_k and its correspondence of reference signals y_k . By using the least squares method, s_k is defined as the solution of

$$\arg\min_{s_k} \sum_{i} \left\{ ([\boldsymbol{y}_k]_i - \tilde{y}_{k-1}) - s_k ([\boldsymbol{x}_k]_i - \tilde{x}_{k-1}) \right\}, \tag{2}$$

where $[x]_i$ means the *i*-th element of x, \tilde{x}_k is the upper bound of the k-th bin, and $\tilde{y}_k = f_k(\tilde{x}_k)$. Based on the above optimization, s_k is serially calculated from k = 1 to K, where $f_1(0) = 0$ is pre-determined and $s_k \ge 0$. At each k, \tilde{y}_k is calculated from s_k and \tilde{x}_k , and then we apply the rounding operation for \tilde{y}_k to be integer for lossless coding and f_k is defined as

$$f_k(x) = \frac{\tilde{y}_k - \tilde{y}_{k-1}}{\tilde{x}_k - \tilde{x}_{k-1}} (x - \tilde{x}_{k-1}) + \tilde{y}_{k-1}.$$
(3)

At the encoder side, we calculate f from the decoded LDR image with the packed HDR image as reference signals, and apply it for the decoded LDR image to produce the degraded HDR image. We apply the rounding operation for the degraded HDR image to have integer values for lossless coding. As the side information, a set of \tilde{y}_k is encoded and stored in the additional file. In this paper, we recalculate the difference between adjacent values in the set, and then the result is encoded by entropy coding. At the decoder side, f is recalculated from the side information and then the degraded HDR image is similarly produced. Using our technique enables, various TMO methods, not only global but also local, to be used to calculate the LDR image from the input HDR image in the first step.

4.4 Gradation Prediction

Gradation prediction is a technique for estimating the input HDR image from the degraded one [36]. In this section, we briefly explain the technique and arrange it to be suitable for the proposed method. For details, readers refer to the paper [36]. The method in [36] consists of two steps: histogram estimation and gradation estimation. First, as the histogram estimation, the method modifies a histogram of the degraded HDR image by the linear interpolation, where the original histogram has a sufficiently minimum width of bins, the number of bins is same as one of pixel values, and the modified histogram has the larger number of bins than the original one. In accordance with the modified histogram, the gradation estimation changes pixel values of the degraded HDR image, and the result is the predicted HDR image.

The authors introduce an evaluation value e_m ($m = 1, 2, \dots, M$) for the m-th pixel, where M is the number of pixels. and the method assigns new values to pixels according to the modified histogram and e_m . On the basis of the simple premise that e_m of a pixel, whose neighbors almost all have high (low) e_m , is also high (low), e_m is defined as

$$e_m = y_m + 1/2^{\alpha - 1} \times [G(Y)]_m,$$
 (4)

where Y, α and $y_m = [Y]_m$ respectively denote the degraded HDR image, its bit depth, and its m-th pixel value, and G is the filtering with the Gaussian kernel. Along the magnitude correlation of e_m , class values of bins c_k ($k = 1, 2, \cdots, K$) in the modified histogram are assigned to pixels, where K is the number of bins, and consequently the histogram of the resultant image is same as the modified one under the same bin width. Unfortunately, the method is not good for the theme discussed in this paper, and it is unsuitable for the premise that the conventional G includes pixels across edges.

To avoid the problem, we use an edge-preserving low-pass filtering as G [37], and propose a modified prediction. As the filter, we simply use a bilateral filter whose size, luminance term parameter and distance term parameter are respectively 7×7 , 1.2, and 0.2. Since the predicted HDR image should have integer values for lossless coding, the modified histogram is restricted to have integer values as c_k . At the histogram estimation, we use the floor function when the linear interpolation is applied for a histogram.

5. Experiments

We compared two cases of the proposed method in experiments with two others respectively cited in [23], [28]. The cases are organized as follows,

Prop. A: Global approximation and Histogram packing,

Prop. B: Three techniques,

i.e., the encoding structure of Prop. B is shown in Fig. 2

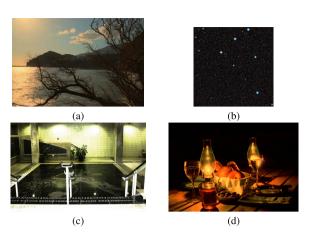


Fig. 4 Specific images for which experiment results are shown in Fig. 5. (a) Agia Galini, (b) Star Field, (c) Atrium, and (d) Still Life.

Table 1 Total bit rates for OpenEXR in [bpp].

Image	Opt. [23]	Basic [28]	Prop. A	Prop. B
Agia Galini	23.42	22.89	14.29	13.86
Atrium Night	27.17	27.33	17.90	17.73
Cafe	26.71	26.61	17.78	17.73
Candle Glass	27.40	27.28	20.35	20.17
Cathedral01	23.93	23.73	15.30	15.02
Cathedral02	24.85	24.85	15.67	15.43
Garden	32.53	32.57	22.89	22.75
Koriyama City	23.67	23.88	15.56	15.21
Snow Road	26.56	26.82	17.62	17.36
Star Field	34.44	36.83	36.97	36.13
Average	26.14	26.19	19.52	19.24

Table 2 Total bit rates for RGBE in [bpp].

Image	Opt. [23]	Basic [28]	Prop. A	Prop. B
Atrium	19.91	13.23	13.51	14.66
Business Statue	22.30	16.55	16.96	16.54
Cathedral	26.48	23.86	17.84	17.55
Chandelier	17.80	13.06	12.42	12.08
Clay People	19.36	14.95	14.26	13.70
Cleanroom	16.62	12.47	12.82	12.92
Couple	16.79	13.63	13.96	13.65
Crane	10.62	8.26	8.42	8.29
Red Barn	14.94	10.89	10.95	10.79
Still Life	41.12	40.07	24.72	24.71
Average	19.60	15.52	14.29	14.15

and it without "Gradation prediction" is one of Prop. A. Since the methods cited in [23], [32] are lossy, we modified them into lossless coding methods based on those respectively cited in Sects. 3.3 and 3.2. In this section, we refer to the methods as the Opt. method [23] and the basic method [28]. The Opt. method is state-of-the-art in 2-layer lossy coding, mentioned in Sect. 2.

The experimental conditions were as follows: The Reinhard global tone-mapping [3] was used as the TMO method in the basic and proposed methods and as the reference TMO of the Opt. method. We used 30 images of OpenEXR and RGBE as input HDR images; some their LDR versions produced by the Reinhard global tonemapping are shown in Fig. 4. LDR and residual images were

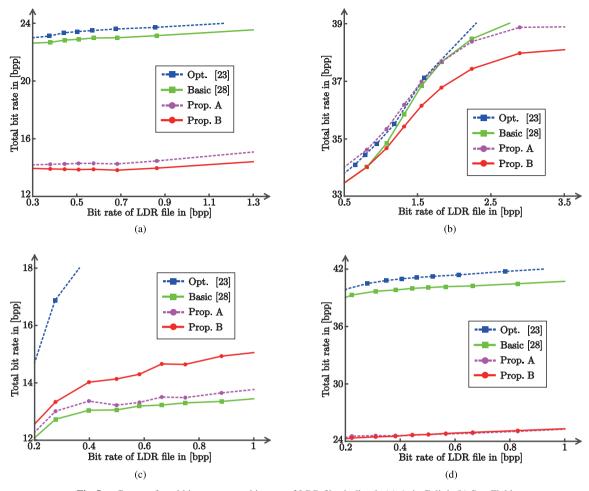


Fig. 5 Curves of total bit rates versus bit rates of LDR files in [bpp]. (a) Agia Galini, (b) Star Field, (c) Atrium, and (d) Still Life.

respectively encoded by JPEG [24] and a lossless mode of JPEG 2k [25]. The side information was encoded by the Huffman coding technique [37] as entropy coding to be stored in additional files Encoded results were measured in bit per pixel (bpp). The bin length δ in Sect. 4.3 was determined as 1.

Note that if the proposed method is actually implemented, we should strictly determine the implementation of coding to losslessly decode HDR images. Two-layer coding use the closed loop strategy, i.e., LDR images are decoded at the encoder side for calculating residual images. Hence, the coding method for LDR images should guarantee to decode same images at both encoder and decoder sides, and we should determine it to satisfy this property.

5.1 Performance for Various Images

We show total bit rates of each method in Tables 1 and 2, where the parameter for the compression quality of JPEG is 50. In the tables, the total bit rate is the sum of the LDR file, the residual file, and the side information (if necessary). "Average" means average results for 30 images.

In OpenEXR, although Prop. B always has better re-

sults than Prop. A, and the difference is usually small for RGBE. Since Prop. B almost always shows better results compared with Prop. A, the gradation prediction slightly contributes for compression. Unfortunately, the gradation prediction requires a larger amount of decoding time than other techniques. Although the histogram packing and the global approximation at the decoder side quickly process by using the side information, the gradation prediction requires the same complexity at both encoder and decoder side.

Compared with conventional methods, the proposed method shows almost always better results for OpenEXR, but its results for RGBE are often comparable with and sometimes better than the basic one. From results, the proposed method is effective for OpenEXR except "Star Field", and we discuss "Star Field" in next section. Although the proposed method is sometimes effective for RGBE, it often has comparable performance with the basic one. However, since the proposed method can use an arbitrary TMO method different from others, we claim that the proposed method is superior to others.

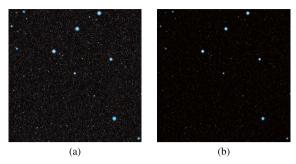


Fig. 6 Tone-mapped images of "Star Field". (a) Reinhard global TMO and (b) TMO of Opt. method.

5.2 Performance for Specific Images at Each Bit Rate of the LDR File

In Fig. 5, we show curves of total bit rates versus bit rates of LDR files. For simplicity, total bit rates and the bit rates of LDR files are called "total rates" and "LDR rates" in this section. The dashed line with square marks, line with square marks, dashed line with circle marks, and line with circle marks show results of the Opt., Basic, Prop. A, and Prop. B methods, respectively. Four graphs correspond to the specific images shown in Fig. 4. In image coding, Rate-Distortion curves are generally shown for discussing coding performance. In this case, however, since HDR images are losslessly encoded and degradations of LDR images resulting from lossy coding depend not on the coding structure but on the TMO method, distortions of HDR images cannot be used and the degradations are unsuitable for making a fair comparison.

From Fig. 5, since the relationship of results does not vary along LDR rates except "Star Field", the effectiveness of the proposed method discussed in Sect. 5.1 is generally valid for various LDR rates. In the case of "Star Field", although the Opt. method has better results than others in Table 1, the proposed method outperforms it in Fig. 5(b). Since "Star Field" is a particular image, the tone-mapping of the Opt. method is not effective for it. Tone-mapped images of "Star Field" by the Reinhard global tone-mapping and the Opt. method are shown in Fig. 6. From the figure, the tonemapped image produced by the Opt. method is blurred and loses small stars. Since the Opt. method regards not only the visual quality of tone-mapped images but also absolute values of residual images, it sometimes produces rough tonemapped images such as "Star Field". Tone-mapped images are expected to have fine textures in 2-layer HDR image coding, and hence the Opt. method is not suitable for "Star Field". Therefore, although the Opt. method has better total bit rates than others in "Star Field", it is not understood that it outperforms others.

6. Conclusion

In this paper, we proposed a 2-layer lossless coding method for high dynamic range (HDR) images that is based on range compression and adaptive inverse tone-mapping. We introduced three techniques it incorporates: histogram packing, global approximation, and gradation prediction. These techniques help the method to reduce the bit depth of residual images and enable it to achieve better compression than conventional methods to which is was compared. In simulation, the proposed method shows better compression ratio than state-of-the-art 2-layer lossless coding methods for OpenEXR, and comparable results for RGBE. Furthermore, it is able to use an arbitrary tone-mapping operation (TMO) method. It can therefore be objectively concluded that the proposed method deserves recognition as the most effective 2-layer lossless coding method yet reported.

Acknowledgements

This work was supported by JSPS KAKENHI Grant Number 26289117 and 16K18104, Research Grants of the Union Tool Scholarship Association.

References

- E. Reinhard, W. Heidrich, P. Debevec, S. Pattanaik, G. Ward, and K. Myszkowski, High Dynamic Range Imaging, Acquisition, Display, and Image-Based Lighting, Second ed, Morgan Kaufmann, CA, 2010.
- [2] F. Banterle, A. Artusi, K. Debattista, and A. Chalmers, Advanced High Dynamic Range Imaging: Theory and Practice, AK Peters, 2011.
- [3] E. Reinhard, M. Stark, P. Shirley, and J. Ferwerda, "Photographic tone reproduction for digital images," ACM Trans. Graph., vol.21, no.3, pp.267–276, 2002.
- [4] E. Reinhard, "Parameter estimation for photographic tone reproduction," J. Graph. Tools, vol.7, no.1, pp.45–52, 2002.
- [5] R. Fattal, D. Lischinski, and M. Werman, "Gradient domain high dynamic range compression," ACM Trans. Graph., vol.21, no.3, pp.249–256, 2002.
- [6] F. Drago, K. Myszkowski, T. Annen, and N. Chiba, "Adaptive log-arithmic mapping for displaying high contrast scenes," Comput. Graph. Forum, vol.22, no.3, pp.419–426, 2003.
- [7] J. Kuang, G.M. Johnson, and M.D. Fairchild, "iCAM06: A refined image appearance model for hdr image rendering," J. Vis. Comun. Image Represent., vol.18, no.5, pp.406–414, 2007.
- [8] Q. Shan, J. Jia, and M.S. Brown, "Globally optimized linear windowed tone mapping," IEEE Trans. Vis. Comput. Graphics, vol.16, no.4, pp.663–675, 2010.
- [9] G. Guarnieri, S. Marsi, and G. Ramponi, "High dynamic range image display with halo and clipping prevention," IEEE Trans. Image Process., vol.20, no.5, pp.1351–1362, 2011.
- [10] S. Paris, S.W. Hasinoff, and J. Kautz, "Local laplacian filters: Edge-aware image processing with a laplacian pyramid," ACM Trans. Graph., vol.30, no.4, pp.68:1–68:12, 2011.
- [11] B. Gu, W. Li, M. Zhu, and M. Wang, "Local edge-preserving multi-scale decomposition for high dynamic range image tone mapping," IEEE Trans. Image Process., vol.22, no.1, pp.70–79, 2013.
- [12] Z. Li and J. Zheng, "Visual salience based tone mapping for high dynamic range images," IEEE Trans. Ind. Electron., vol.61, no.12, pp.7076–7082, 2014.
- [13] K. Ma, H. Yeganeh, K. Zeng, and Z. Wang, "High dynamic range image compression by optimizing tone mapped image quality index," IEEE Trans. Image Process., vol.24, no.10, pp.3086–3097, 2015.
- [14] G. Ward and M. Simmons, "JPEG-HDR: A backwards-compatible,

- high dynamic range extension to JPEG," Proc. ACM SIGGRAPH 2006 Courses, 2006.
- [15] M. Okuda and N. Adami, "Two-layer coding algorithm for high dynamic range images based on luminance compensation," J. Visual Commun. Image Represent., vol.18, no.5, pp.377–386, 2007.
- [16] I.R. Khan, "Two layer scheme for encoding of high dynamic range images," Proc. IEEE Int. Conf. Acoustics Speech Signal Process., pp.1169–1172, 2008.
- [17] A. Boschetti, N. Adami, R. Leonardi, and M. Okuda, "Flexible and effective high dynamic range image coding," Proc. IEEE Int. Conf. Image Process., pp.3145–3148, 2010.
- [18] T. Ito, Y. Bandoh, T. Seishi, and H. Jozawa, "A coding method for high bit-depth images based on optimized bit-depth transform," Proc. IEEE Int. Conf. Image Process., pp.3141–3144, 2010.
- [19] Z. Mai, H. Mansour, R. Mantiuk, P. Nasiopoulos, R. Ward, and W. Heidrich, "Optimizing a tone curve for backward-compatible high dynamic range image and video compression," IEEE Trans. Image Process., vol.20, no.6, pp.1558–1571, 2011.
- [20] Y. Zhang, E. Reinhard, and D.R. Bull, "Perceptually lossless high dynamic range image compression with JPEG 2000," Proc. IEEE Int. Conf. Image Process., pp.1057–1060, 2012.
- [21] T. Jinno, M. Okuda, and N. Adami, "New local tone mapping and two-layer coding for HDR images," Proc. IEEE Int. Conf. Acoustics Speech Signal Process., pp.765–768, 2012.
- [22] T. Fujiki, N. Adami, T. Jinno, and M. Okuda, "High dynamic range image compression using base map coding," Proc. Asia-Pacific Signal Inf. Process. Assoc. Annual Summit Conf., pp.1–4, 2012.
- [23] A. Koz and F. Dufaux, "Methods for improving the tone mapping for backward compatible high dynamic range image and video coding," Signal Process.-Image Commun., vol.29, no.2, pp.274–292, 2014.
- [24] ISO/IEC 10918, Information technology Digital compression and coding of continuous-tone still images.
- [25] ISO/IEC 15444, Information technology JPEG 2000 image coding system.
- [26] ISO/IEC 21992, Information technology JPEG XR image coding system.
- [27] ISO/IEC 15948, Information technology Computer graphics and image processing - Portable Network Graphics (PNG).
- [28] M. Iwahashi, T. Yoshida, N. Mokhtar, and H. Kiya, "Bit-depth scalable lossless coding for high dynamic range images," EURASIP J. Adv. Signal Process., vol.2015, no.1, 2015.
- [29] M. Iwahashi, H. Kobayashi, and H. Kiya, "Lossy compression of sparse histogram image," Proc. IEEE Int. Conf. Acoustics Speech Signal Process., pp.1361–1364, 2012.
- [30] M. Iwahashi and H. Kiya, "Two layer lossless coding of HDR images," Proc. IEEE Int. Conf. Acoustics Speech Signal Process., pp.1340–1344, 2013.
- [31] T. Odaka, W.S. Tang, M. Fujiyoshi, H. Kobayashi, M. Iwahashi, and H. Kiya, "An efficient lossless compression method using histogram packing for HDR images in OpenEXR format," IEICE Trans. Fundamentals., vol.E97-A, no.11, pp.2181–2183, Nov. 2014.
- [32] R. Xu, S.N. Pattanaik, and C.E. Hughes, "High-dynamic-range still-image encoding in JPEG 2000," IEEE Comput. Graph. Appl., vol.25, no.6, pp.57–64, 2005.
- [33] N. Sugiyama, H. Kaida, X. Xue, T. Jinno, N. Adami, and M. Okuda, "HDR image compression using optimized tone mapping model," Proc. IEEE Int. Conf. Acoustics Speech Signal Process., pp.1001–1004, 2009.
- [34] ISO/IEC 18477, Information technology Scalable compression and coding of continuous-tone still images.
- [35] A.J. Pinho, "An online preprocessing technique for improving the lossless compression of images with sparse histograms," IEEE Signal Process. Lett., vol.9, no.1, pp.5–7, 2002.
- [36] M. Takeuchi, Y. Matsuo, Y. Yamamura, J. Katto, and K. Iguchi, "A bit-depth scalable video coding approach considering spatial gradation restoration," Proc. IEEE Int. Conf. Acoustics Speech Signal Process., pp.1373–1376, 2012.

[37] R.C. Gonzalez and R.E. Woods, Digital Image Processing, Prentice Hall, 2002.



Taichi Yoshida received B.Eng., M.Eng. and Ph.D. degrees in Engineering from Keio University, Yokohama, Japan, in 2006, 2008, and 2013. In 2014, he joined Nagaoka University of Technology, where he is currently an Assistant Professor in the Department of Electrical, Electronics and Information Engineering, Faculty of Technology. His research interests are in the field of filter bank design, image coding, and image processing.



Masahiro Iwahashi received his B.E., M.E., and D.E. degrees in Electrical Engineering from Tokyo Metropolitan University in 1988, 1990, and 1996. In 1990, he joined Nippon Steel Co., Ltd.. From 1991 to 1992, he was seconded to Graphics Communication Technology Co., Ltd.. In 1993, he joined Nagaoka University of Technology, where he is currently a Professor in the Department of Electrical, Electronics and Information Engineering, Faculty of Technology. From 1995 to 2001, he was also a lecturer at the

Nagaoka Technical College. From 1998 to 2001, he relocated to Thammasat University, Thailand, and to the Electronic Engineering Polytechnic Institute of Surabaya, Indonesia, as a JICA expert. His research interests are in the areas of digital signal processing, multi-rate systems, and image compression. He served as an editorial committee member of the Transaction on Fundamentals of the IEICE from 2007 to 2011.



Hitoshi Kiya received his B.Eng. and M.Eng. degrees from Nagaoka University of Technology, Japan in 1980 and 1982 and his Dr.Eng. degree from Tokyo Metropolitan University in 1987. In 1982, he joined Tokyo Metropolitan University as an Assistant Professor, and was promoted to Professor in 2000. From 1995 to 1996, he attended the University of Sydney, Australia as a Visiting Fellow. He currently serves as the Chair of the IEEE SPS Japan Chapter, and an Associate Editor of IEEE

Trans. Image Processing and IEEE Trans. Information Forensics and Security. He previously served as the President of IEICE ESS, an Associate Editor of IEEE Trans. Signal Processing, the Editor-in-Chief of IEICE Fundamentals Review, a Vice President of APSIPA, a Member of the Board of Governors of APSIPA, and Chair of the Publications Board of IEICE ESS. His research interests are in the area of signal and image processing including multirate signal processing, wavelets, video coding, compressed-domain video manipulation and security for multimedia. He received the ITE Niwa-Takayanagi Best Paper Award in 2012, the Telecommunications Advancement Foundation Award in 2011, the IEICE ESS Contribution Award in 2010, and the IEICE Best Paper Award in 2008. He is a Fellow Member of the ITE and a Senior Member of the IEEE.