Two Layer Coding of HDR Images with Noise Bias Compensation

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***Abstract*— This paper introduces a noise bias compensation (NBC) to a two layer backward compatible high dynamic range (HDR) image coding to decrease data volume of the compressed data. In this system, dynamic range of the input HDR image is reduced with tone mapping (TM) to generate a low dynamic range (LDR) image. It is encoded to generate a bit stream in the base layer. In the enhancement layer, quantization noise added by lossy coding of the LDR image is amplified by the inverse of TM. It brings about much bit rate in this layer. To cope with this problem, this paper introduces NBC to reduce variance of the noise. It compensates noise bias (NB) according to an observed pixel value. In this paper, NB is defined as the mean of the noise in the same observed pixel value from different original values. It is experimentally observed that the proposed method significantly reduces data volume in the enhancement layer at high quality lossy coding of LDR images.**

I. INTRODUCTION

Tone mapping (TM) plays an important role in adjusting image quality. It is also necessary to design a suitable mapping function to convert a high dynamic range (HDR) image to a low dynamic range (LDR) image [1-4]. In a two layer backward compatible HDR image coding system, two kinds of bit streams are produced [5-8]. One is for decoding the LDR image in the base layer, and the other is for the HDR image in the enhancement layer. In the latter layer, it is required to reduce the quantization noise added by lossy coding of the LDR image. However the noise is amplified by the inverse of TM. As a result, the data volume of the bit stream in the enhancement layer is increased.

This paper aims at decreasing the bit rate in the enhancement layer introducing the noise bias compensation (NBC). Note that the noise bias (NB) referred to in this paper does not mean the average of the noise over all pixels in an image. It is defined as the mean over pixel values in a subset in which all elements share the same observed pixel value. Most of the literatures assume zero mean of the noise in designing a filter [9]. So far, numerous attempts have been done in de-noising such as the classical regression filters [10,11]. The photometric distance has been taken into account in the bilateral filters [12,13]. The non-local mean (NLM) filter replaces pixel-wise calculation of the distance with patch-wise one [14-16]. However, little attention has been paid to the NB.

Unlike these previous reports, this paper discusses on the non-zero value of NB. Recently, an idea of noise bias compensation (NBC) was reported to improve quality of a tone mapped noisy image [17]. It makes NB approximately zero by subtracting estimation of NB from the observed pixel value. This paper tries to reduce the data volume of the bit stream of the enhancement layer introducing NBC to the two layer backward compatible HDR image coding. The NBC in this paper is extended from [17] so that it is especially adjusted for the two layer coding [7,8].

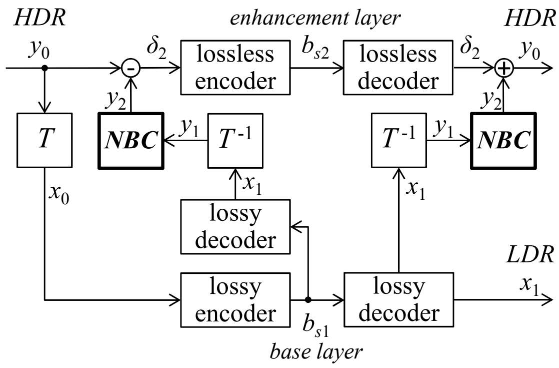


Fig.1 Noise Bias Compensation (NBC) is introduced to the two layer backward compatible HDR image coding.

II. PROBLEM SETTING

A. Two Layer HDR Image Coding

Figure 1 illustrates the backward compatible two layer HDR image coding [7,8]. The input HDR image y_0 is tone mapped with a function f to generate an LDR image x_0. It is compressed with a lossy encoder to generate a bit stream b_{s1} in the base layer. In decoder, the LDR image x_1 is reconstructed. The encoder also generates another bit stream b_{s2} in the enhancement layer. Note that this system decodes the HDR image without any loss (lossless). This paper aims at reducing the data volume of b_{s2} introducing NBC to the system.

Procedure inside the system is detailed as below. A pixel value y_0 of the input HDR image is tone mapped to a pixel value x_0 of the LDR image as

$$x_0 = T[y_0] = R_x[f(y_0)], \quad y_0 \in [0, M_y] \tag{1}$$

where $R_x[\ ]$ denotes rounding to integer and clipping to the range of $[0,M_x]$. As an example, this paper uses the Hill function defined as

$$f(y_0)=M_x\cdot\left\{1+\left(b\cdot\frac{\bar{y}_0}{y_0}\right)^a\right\}^{-1} \tag{2}$$

where $\bar{y}_0$ denotes the geometric mean of pixel values. The tone mapped image is encoded with a lossy encoder and decoded in the base layer. The decoded pixel value x_1 contains the quantization noise added in this coding process. The quantization contributes to compressing the data volume of the base layer. However it increases the bit rate (the data volume of b_{s2}) of the enhancement layer. The decoded pixel value x_1 is inversely tone mapped to y_1. In the existing system, the residual $\delta_1 = y_1 - y_0$ is encoded. If y_1 is a good approximation of y_0, the variance of δ_1 becomes small, so as the bit rate in this layer. This paper applies NBC to generate a better approximation y_2 to decrease its data volume.

B. *Model of the Noise Bias Compensation (NBC)*

Figure 2 illustrates a model of NBC for analysis. A pixel value y_0 is tone mapped to x_0 with a function f as described in (1). In the lossy coding process, a scalar x_0 is mapped to a random variable x_1 by adding the input noise ε_1 as

$$x_1 = x_0 + \varepsilon_1\,. \tag{3}$$

It is inversely tone mapped as

$$y_1 = T^{-1}(x_1) = y_0 + \delta_1 \tag{4}$$

where δ_1 is the residual to be reduced and $T^{-1}[\ ]$ denotes the inverse of the tone mapping in (1). Note that ε_1 and δ_1 are supposed to be random variables. This paper applies NBC as

$$y_2 = y_1 - h(y_1) = y_0 + \delta_2 \tag{5}$$

with a newly introduced function h. It aims at reducing the variance of δ_2 defined as

$$Var[\delta_2] = \int P(\delta_2)\left(\delta_2 - \bar{\delta}_2\right)^2 d\delta_2 \tag{6}$$

for

$$\bar{\delta}_2 = \int P(\delta_2)\delta_2 d\delta_2 \tag{7}$$

where $P(\delta_2)$ denotes the probability density function (PDF) of the output noise δ_2.

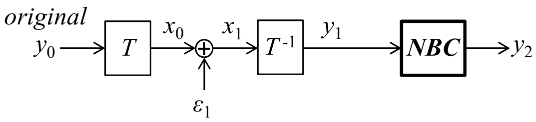


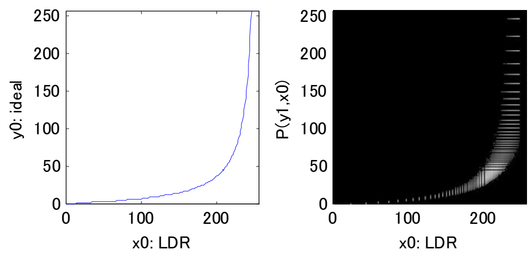
Fig.2 A model of the 'Noise Bias Compensation' (NBC).

C. *Noise Bias (NB) after Tone Mapping (TM)*

Figure 3(a) illustrates an example of TM. Parameters in (2) are set to M_x=255, a=b=1 and $\bar{y}_0$=10, respectively. Fig. 3(b) illustrates the joint PDF $P(x_0, y_1)$ of x_0 and y_1 in log scale. As an example, PDF of the input noise ε_1 is given as

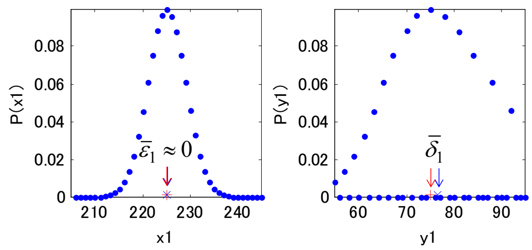
$$P(\varepsilon_1\,|\,x_0)=\begin{cases}\dfrac{1}{\sqrt{2\pi}\sigma}\exp\dfrac{-\varepsilon_1^{\,2}}{2\sigma^2} & ,\ x_0\in[\varepsilon_1, 255-\varepsilon_1]\\ 0 & ,\ x_0\notin[\varepsilon_1, 255-\varepsilon_1]\end{cases} \tag{8}$$

with the variance $\sigma^2=4^2$. This is one of the prior information to be used in NBC. An observed or an appropriately modelled PDF is used in practice. Fig. 4(a) illustrates PDF of x_1 at x_0 =225. The mean of x_1 is 225.01. Fig. 4(b) illustrates PDF of y_1 at $y_0=T^{-1}(225)$ =75. The mean of y_1 is 76.58. This means that NB 'after' TM is non-zero even though NB 'before' TM is almost zero. This is due to non-linearity of TM. In NBC, PDF of the input pixel values x_0 and that of the input noise ε_1 (or their approximations) are used as 'prior information' to design the function h in (5).



(a) (b)

Fig.3 An example of TM. (a) Input value x_0 is tone mapped to y_0. (b) Log-scaled $P(x_0, y_1)$. Input value x_0 is mapped to a random variable y_1.



(a) (b)

Fig.4 Probability density function (PDF) of random variables x_1 and y_1 at (x_0, y_0) =(225, 75). NB after TM is 76.58 -75 =+1.58.

III. Proposed Method

A. *Definition of Noise Bias (NB)*

Definition of NB in this paper is not the same as the mean in (7). It is defined as

$$\bar{\delta}_1(y_1)=\frac{\int P(x_0,y_1)\delta_1 dx_0}{P(y_1)} \tag{9}$$

where $P(x_0, y_1)$ denotes the joint probability density function of x_0 and y_1. It means the average of the noise δ_1 in an observed pixel value y_1 at different locations from different original values x_0. Note that δ_1 and y_1 are considered to be random variables. Substituting

$$P(x_0, y_1) = P(x_0 \mid y_1)P(y_1) \tag{10}$$

into (9), NB becomes

$$\overline{\delta_1}(y_1) = \int P(x_0 \mid y_1)\delta_1 dx_0 \tag{11}$$

which means the conditional mean of the output noise δ_1 for the same observed value y_1.

B. NBC in the Proposed Method

NBC tries to make NB in (11) zero for each of the observed value y_1 by the compensation in (5) so that the variance in (6) becomes small [17]. In the proposed method, NB is compensated with

$$h(y_1) = \int P(x_0 \mid y_1)\left\{y_1 - T^{-1}(x_0)\right\}dx_0 \tag{12}$$

which is identical to the estimate in (11). Substituting

$$P(y_1) = \int P(x_0, y_1)dx_0 \tag{13}$$

and (10) into (12), the compensation function is derived as

$$h(y_1) = \frac{\int P(x_0, y_1)\left\{y_1 - T^{-1}(x_0)\right\}dx_0}{\int P(x_0, y_1)dx_0}\ . \tag{14}$$

It means the centroid of the output noise δ_1 in (4). In this calculation, the prior knowledge $P(x_0, y_1)$ in Fig. 3(b) is used as weighting of the output noise.

C. Modelling of PDF

According to the Bayesian inference, the compensation in (14) is expressed as

$$h(y_1) = \frac{\int P(y_1 \mid x_0)P(x_0)\left\{y_1 - T^{-1}(x_0)\right\}dx_0}{\int P(y_1 \mid x_0)P(x_0)dx_0}\ . \tag{15}$$

Since $P(y_1 \mid x_0)$ is identical to $P(\delta_1 \mid x_0)$, when

$$P(\delta_1 \mid x_0) \cong P(\varepsilon_1 \mid x_0) \cdot \left\{\frac{df}{dx}\right\}^{-1} \tag{16}$$

holds, the estimate in (15) can be calculated with $P(x_0)$ and $P(\varepsilon_1 \mid x_0)$. Namely, the proposed method estimates NB with PDF of the image pixel value x_0 and that of the noise ε_1 under a given TM function f. Note that a mapping table from an integer y to an integer $h(y)$ is required to be included into the bit-stream as a side information in implementation.

IV. Experimental Results

A. Conditions

Effect of NBC on reducing data volume of the bit stream in the enhancement layer is investigated. Scaled integer pixel values y_0 of the original pixel values w_0 in OpenEXR or RGBE images are tested. The scaling was performed as

$$y_0 = \begin{cases} R\left[\dfrac{M_y \cdot (w_0 - Mn)}{Mx - Mn}\right] & ,\ w_0 \in [Mn, Mx] \\ 0 & ,\ w_0 < Mn \\ M_y & ,\ w_0 > Mx \end{cases} \tag{17}$$

where

$$\begin{cases} Mn = \min\{w_0 \mid w_0 > 0\} \\ Mx = \min\{w_0 \mid F(w_0) \geq 0.999\} \end{cases}$$

and

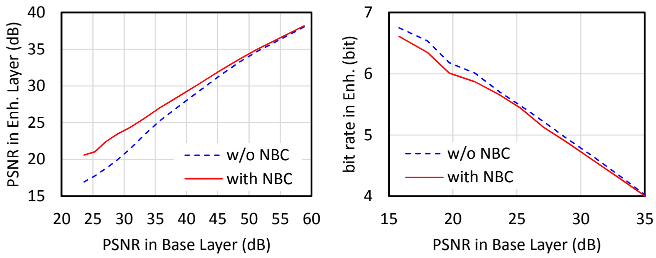
$$F(w_0) = \int_{-\infty}^{w_0} P(w)dw\ .$$

In the equations above, $P(w_0)$ denotes PDF of w_0 and $F(w_0)$ denotes the cumulative distribution function, respectively. In (17), pixel values are rounded to $\log_2 M_y$ bit depth integers with a rounding operator $R[\ ]$. In the following experiments, the bit stream in the base layer was generated with the JPEG encoder. The dynamic range was set to (M_x, M_y)=(255, 1023).

B. Evaluation of the System for Images

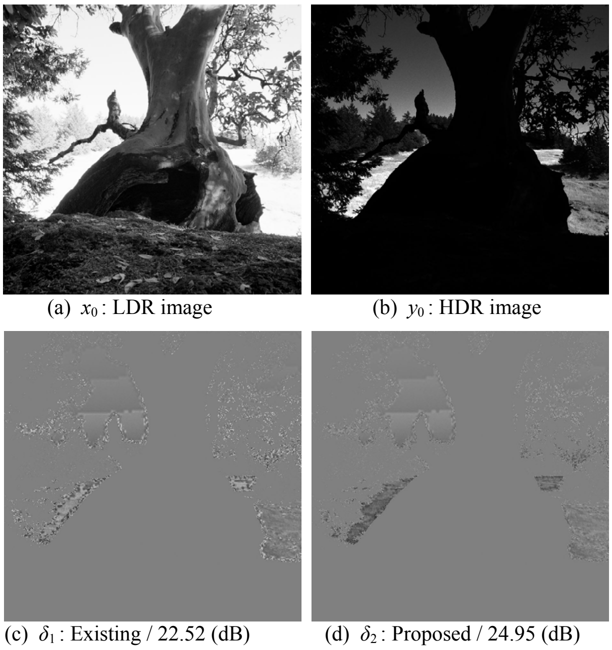
Figure 5(a) indicates how the variance (measured with PSNR) of the residual in the enhancement layer is reduced by NBC. The horizontal axis indicates the variance (measured with PSNR) of the decoded image in the base layer. It was observed that NBC decreases the variance of the residual at low PSNR of decoded images (at low bit rate coding) of the base layer. Figure 5(b) indicates the bit rate of the enhancement layer. It was observed that NBC decreases the bit rate at low bit rate coding of the base layer. Unfortunately, effect on the bit rate is limited to small amount, even though the variance is significantly reduced. In these Figures, an input image 'Tree' in the OpenEXR was used. The LDR image x_0 and the HDR image y_0 is indicated in Figure 6(a) and 6(b), respectively. The residual to be encoded in the enhancement layer of the existing method and the proposed method is indicated in Figure 6(c) and 6(d), respectively. The variance of δ_2 of the proposed method became smaller than that of δ_1 of the existing method.

Figure 7 indicates PSNR of the residual in the enhancement layer for various input images at different level of the quantization step size in lossy coding of the base layer. The PSNR of the decoded images in the base layer is 43 (dB) and 30 (dB) in average in Figure 7(a) and 7(b), respectively. It was confirmed that NBC contributes to reduce the variance of the residual in the enhancement layer.



(a) (b)

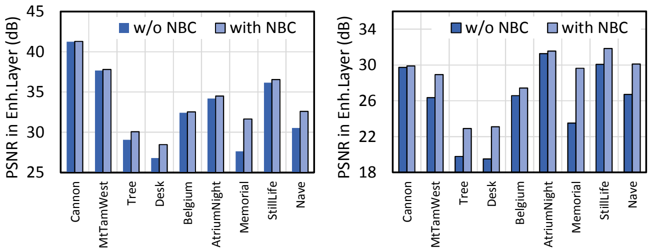
Fig.5 The variance and the data volume of the enhancement layer.



(a) x_0 : LDR image (b) y_0 : HDR image

(c) δ_1 : Existing / 22.52 (dB) (d) δ_2 : Proposed / 24.95 (dB)

Fig.6 Example of processed images for 'Tree'.



(a) (b)

Fig.7 The variance (in log scale) of the enhancement layer.

V. CONCLUSIONS

A simple NBC method for the two layer HDR coding was proposed. It was confirmed that NBC has positive effect on bit rate saving especially at low bit rate lossy coding of LDR images. Since the experiments is limited to lossless coding of HDR images, it should be extended to lossy coding of HDR images. Since the rounding errors are neglected, analysis on effect of the rounding [18] should be also considered in the near future.

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