Local Inverse Tone Mapping for Scalable High Dynamic Range Image Coding

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***Abstract*—Tone mapping operators (TMOs) and inverse tone mapping operators (iTMOs) are important for scalable coding of high dynamic range (HDR) images. Because of the highly non-linearity of local TMOs, it is very difficult to estimate the iTMO accurately for a local TMO. In this paper, we present a two-layer local iTMO estimation algorithm using an edge-preserving decomposition technique. The low dynamic range (LDR) image is first linearized and then decomposed into a base layer and a detail layer via a fast edge-preserving decomposition method. The base layer of the HDR image is generated by subtracting the LDR detail layer from the HDR image. An iTMO function is finally estimated by solving a novel quadratic optimization problem formulated on the pair of base layers rather than the pair of HDR and LDR images as in existing methods. Experimental results show that the proposed two-layer iTMO can recover the HDR accurately so that it is possible to use these local TMOs in scalable HDR image coding schemes.**

***Index Terms*—High Dynamic Range, Tone Mapping, Inverse Tone Mapping, Edge-preserving Decomposition, Scalable Coding.**

I. Introduction

SCALABLE coding schemes [1], [2] provide a possible backward compatible solution to distribute a high dynamic range (HDR) image in the transition phase from low dynamic range (LDR) displays to HDR displays. The flow of this scalable coding is shown in Fig. 1. As shown in the flow, two bitstreams are transmitted to the decoder. The base layer bitstream contains the tone mapping result of the LDR image which is obtained by using an arbitrary tone mapping operator (TMO) according to a user's preference [3]–[5]. The enhancement layer bit-stream contains the meta data to recover the HDR image, such as the parameters of the inverse TMO (iTMO) and the residual of the HDR image and the inverse tone-mapped LDR image. In the decoder side, LDR users only decode the base layer bitstream to view the tone mapping result on the LDR displays while HDR users decode all bitstreams to reconstruct the HDR image transmitted and reproduce it on the HDR displays. Under such scalable coding framework, the TMO determines the appearance of the base layer which is intended for the LDR users while the iTMO affects the bit-rate for the enhancement layer. A more accurate iTMO requires fewer bits to encode the residual.

Currently, several scalable coding schemes have been proposed based on the global TMO and its iTMO because of the efficiency and reversibility of global TMOs [6]–[8]. These methods are almost real-time and achieve a low bit-rate for the enhancement layer. However, the global TMOs [9], [10] cannot produce as good looking results as local TMOs [11]–[15] in terms of detail preservation. Thus from such a consideration, the global TMO based scalable coding schemes might not be friendly to LDR users. Local TMO based scalable coding schemes are demanded to provide better user experience for LDR users. Unfortunately, it is very difficult to estimate the local iTMO because a local TMO is a function of both luminance and local contrast. Directly modeling a local iTMO as a mapping from LDR luminance to HDR luminance results in inaccurate estimations [7], [16]. Assuming that pixels within a small neighborhood have the same local contrast, a local iTMO can be simplified as a mapping function block-wisely. An example is reported in [17], by modelling a local iTMO as a number of global iTMOs which are estimated using the pair of HDR and its tone-mapped LDR patches for each block. Actually, it is noted that if the local contrast for each pixel of the tone-mapped image is nearly zero, the local iTMO can be simplified as a mapping function globally. Following this idea, we believe that an edge-preserving smoothing technique can be employed to obtain a piece-wise smooth version of the tone-mapped image for developing a local iTMO globally. However, to the best of our knowledge, no work has been done on estimating a local iTMO using such technique.

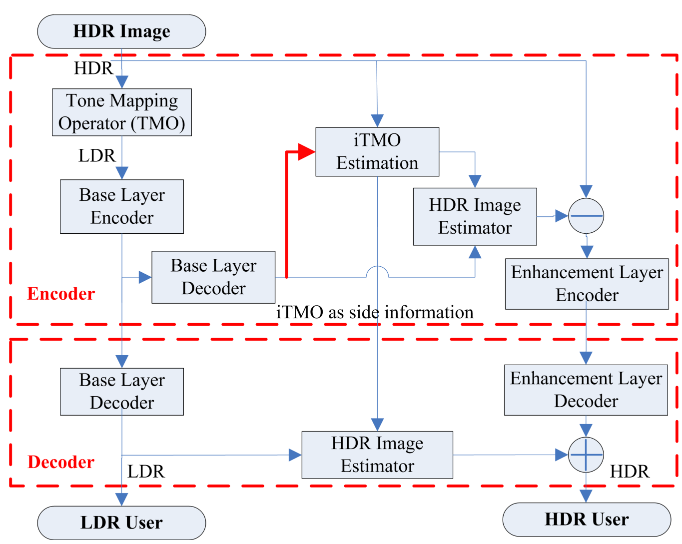

Fig. 1. Workflow of scalable coding for HDR images.

In this paper, we propose a two-layer local iTMO by using a fast edge-preserving decomposition technique. The proposed

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iTMO is inspired by the local TMOs [12]–[15], [18], [19] which are designed based on an edge-preserving decomposition of the HDR image. In these local TMOs, an HDR image is decomposed into a base layer and a detail layer via an edge-preserving smoothing filter. The base layer which is piece-wise smooth and contains dynamic range information is compressed via a global TMO while the detail layer is preserved to keep local contrast. Thus it is reasonable to take the decomposition into consideration when a local iTMO is designed. Unlike the local TMO, the linearized LDR image instead of the HDR image is decomposed into a base layer and a detail layer in logarithmic domain by using the fast WLS in [15] in the proposed method. The base layer of the HDR image is generated by subtracting the detail layer of the linearized LDR image from the HDR image in logarithmic domain. An iTMO function is estimated using the pair of base layers rather than the pair of HDR and LDR images themselves as in existing methods. The estimation of the iTMO function between the pair of base layers is similar to the estimation of camera response functions (CRFs) among multiple differently exposed LDR images. Inspired by the method in [20] which shows that the CRF and the global tone mapping function share the same property of smooth and monotonous increasing, a novel quadratic optimization problem is formulated to estimate the iTMO function between the pair of base layers. It is worth noting that other existing CRF estimation methods such as [21], [22] are also applicable. With the iTMO function and the edge-preserving decomposition of the linearized LDR image, an HDR image can be estimated in the decoder side by using the decoded LDR image only. The proposed local iTMO is simple and fast so that it is applicable to the compression of HDR images. Our preliminary study shows that the proposed iTMO can be applied to improve the coding efficiency of scalable HDR image coding.

The rest of the paper is outlined as follows. The edge-preserving decomposition based local TMOs are summarized in Section 2 and the two-layer local iTMO is introduced in Section 3. Experimental results are shown in Section 4 and conclusion and remarks are given in Section 5.

II. Local Tone Mapping Operators

In this paper, the edge-preserving decomposition based local TMOs [12]–[15] are mainly investigated. Denote the logarithmic of the luminance of the HDR image and the tone-mapped LDR image as Y and X, respectively. In these local TMOs, Y is decomposed into a base layer Y_b and a detail layer Y_d as $Y = Y_b + Y_d$. The base layer Y_b is obtained by edge-preserving filters in [12]–[15]. It is piece-wise smooth and contains large-scale variations such as sharp edges and therefore dynamic range information. Thus it can be compressed to reduce the dynamic range. On the other hand, Y_d contains small-scale variations such as details and is kept to preserve local contrast. Based on such considerations, we have

$$X_b = f(Y_b); \quad X_d = \theta Y_d, \tag{1}$$

where X_b and X_d are the base layer and detail layer of the tone-mapped image, respectively, $f(\cdot)$ is a global TMO, for example the one in [10], and θ is a scaler as in $[1, 2]$ to amplify the detail layer [18], [19].

Under this edge-preserving decomposition based local tone mapping framework, the quality of decomposition could affect the tone mapping result significantly. Local edge-preserving filters such as bilateral filter (BF) [12] and guided image filter [13], [23] cannot always preserve edges well so that halos could be produced [13]. Global edge-preserving filters such as weighted least square (WLS) [14] can produce a halo-free tone mapping result but it is very slow. The fast WLS (FWLS) [15], which is a fast approximation of WLS, produces a similar smoothing result of the WLS with a competitive speed to the BF [12] and the GIF [13] so that it is selected as an example to illustrate the proposed local iTMO.

III. Two-layer Local Inverse Tone Mapping

The flow of the proposed iTMO function estimation is shown in Fig. 2 and HDR image estimation using the iTMO function is shown in 3. The base layer of the HDR image is obtained by expanding the dynamic range of the base layer of the decoded LDR image with an iTMO function which is transferred from the encoder side to the decoder side. And the detail layer of the LDR image is directly used to estimate the detail layer of the HDR one.

A. Generation of a Pair of Base Layers

The FWLS in [15] is adopted to decompose the linearized LDR image which is obtained by gamma correction with the value of gamma as 2. According to [14], the base layer X_b can be obtained by solving the following optimization problem:

$$\arg\min_{X_b} \sum_p \{(X_b(p) - X(p))^2 + \lambda \sum_{q \in N(p)} \omega_{p,q} \left(X_b(p) - X_b(q)\right)^2\} \tag{2}$$

where p is the location of the pixel, $N(p)$ is the set of the right and bottom pixels of pixel p and $\omega_{p,q}$ is defined as $\omega_{p,q} = (\|X(p) - X(q)\| + \epsilon)^{-\alpha}$ where ϵ is a small number to avoid division by 0. α controls the smoothness of the result and is selected as 1.2. Parameter λ determines the smoothness of the X_b. A larger λ results in a smoother X_b. In our experiments, we fix λ as 1 for all images for the separation of base and detail layers. The FWLS [15] solves Eq. (2) in a separable manner. An intermediate smoothing result is first obtained by solving the optimization problem along horizonal direction. Then the intermediate result is smoothed along vertical direction. When smoothing along the horizonal direction, an optimization problem is formulated for each row. Denote the ith row of the base layer and the LDR image as X_b^i and X^i respectively. The smoothing problem for ith row is formulated as

$$\arg\min_{X_b^i} \sum_x \{(X_b^i(x) - X^i(x))^2 + \lambda_k \omega_{x,x+1} (X_b^i(x) - X_b^i(x+1))^2\} \tag{3}$$

where λ_k is the parameter for kth iteration, and it is defined as $\lambda_k = \frac{3}{2}\frac{4^{T-k}}{4^T - 1}\lambda$. The WLS is accelerated because the closed-form solution of Eq. (3) is equivalent to solving a small scale linear system with a tri-diagonal coefficient matrix. In addition, since the optimization problem is formulated for each row, the fast WLS can be further accelerated using the parallel computing techniques. The formulation of the smoothing along vertical direction is similar to Eq. (3).

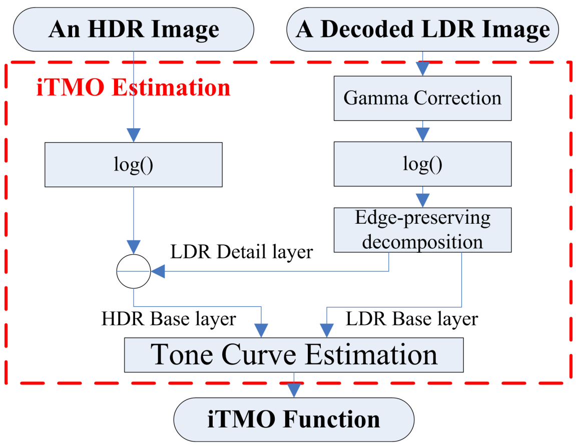

Fig. 2. Workflow of iTMO estimation in encoder side.

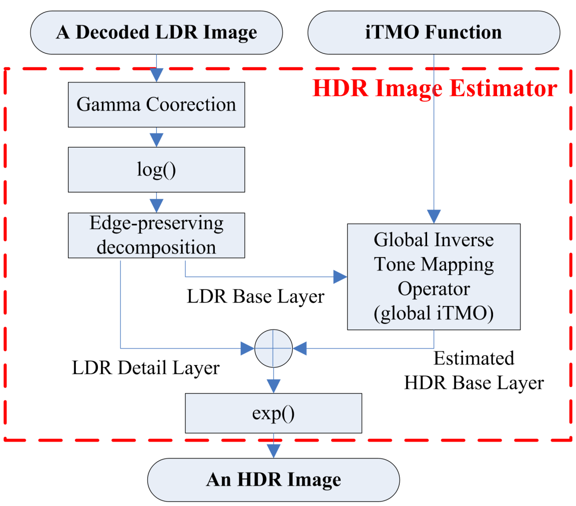

Fig. 3. Workflow of HDR image estimation via the proposed two-layer iTMO.

B. Tone Curve Estimation

The iTMO function is estimated using the pair of base layers of the HDR image and its tone-mapped LDR image as shown in Fig. 2 in the encoder side. The LDR image is linearized by gamma correction. After decomposing the linearized LDR image into a base layer and a detail layer using the FWLS filter, the detail layer of the LDR image is subtracted from the HDR image in logarithmic domain to generate the base layer of the HDR image:

$$Y_b = Y - X_d. \tag{4}$$

Because the global TMO in Eq. (1) adjusts HDR luminance using a monotonous increasing function, the inverse function is well-defined. It is worth noting that the CRFs among differently exposed LDR images are also monotonous increasing. It is expected that existing CRF estimation methods such as the one in [20] can be extended to estimate the iTMO function. Based on this observation, a new quadratic optimization problem is formulated as

$$E(G) = \sum_{i=1}^{n}\{w(X_b(i))(g(X_b(i))-Y_b(i))^2\}+\mu\sum_{j=x_{min}+1}^{x_{max}-1} w(j)g''(j)^2, \tag{5}$$

where n is the number of pixels, i is the index of the pixel, $g(\cdot)$ is the global iTMO function, X_b is the base layer of the LDR image and Y_b is the base layer of the HDR image. The first term ensures that the estimated image using the iTMO function is close to the original HDR data and the second term ensures the smoothness of the iTMO function. Weight w is introduced because the iTMO function may fit data more poorly when near extremes. When $\mu = 0$, Eq. (5) may become ill-posed when the number of pixels in some bins is nearly zero. To avoid this problem, we set $\mu = 1000$ in our implementation for all experiments. Note that without w and the smoothness term, Eq. (5) becomes the same fitting problem as in [7]. We quantize X_b into 256 levels so that $x_{min} = 0$ and $x_{max} = 255$. Like the global TMO, the global iTMO function can also be implemented using a look-up table. Denote the look-up table as a vector $G = [g(0) \quad g(1) \quad \cdots \quad g(255)]^T$. The second order derivative $g''(j)$ is computed as $g''(j) = g(j-1) - 2g(j) + g(j+1)$. $w(i)$ is introduced to penalize near-saturated pixels and it is defined as

$$w(i) = \begin{cases} i, i \in [0, 127] \\ 255 - i, i \in [128, 255]. \end{cases} \tag{6}$$

Now we define the following three matrices: an $n*n$ diagonal matrix W $W(i,i) = w(X_b(i))$, an $n*256$ matrix H

$$h_{i,j} = \begin{cases} 1, if \;\; X_b(i) = j-1 \\ 0, otherwise \end{cases} \tag{7}$$

and a $254*256$ matrix M

$$M = \begin{bmatrix} 1 & -2 & 1 & \ldots & 0 & 0 \\ 0 & 1 & -2 & 1 & \ldots & 0 \\ \vdots & \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \ldots & 1 & -2 & 1 \end{bmatrix} \tag{8}$$

Then the vector form of the energy function is represented as

$$E(G) = (HG-Y)^T W(HG-Y) + \mu(MG)^T \hat{W} MG \tag{9}$$

where $\hat{W} = diag\{w(1), w(2), \cdots, w(254)\}$. Let $\frac{\partial E(G)}{\partial G} = 0$. We have

$$(H^T WH + \mu M^T \hat{W} M)G = H^T WY. \tag{10}$$

Denote H as $H = [h_{c_1} \; h_{c_2} \; \ldots \; h_{c_{256}}]$, where h_{c_i} is the ith column of H. Because for each row of H, only one element is non-zero which is 1, thus

$$h_{c_i}^T * h_{c_j} = \begin{cases} n_{i-1}, if \;\; i = j \\ 0, otherwise \end{cases} \tag{11}$$

where n_{i-1} is the number of pixels with intensity $i-1$. Therefore

$$H^T WH = diag\{w_0 * n_0, w_1 * n_1, \ldots, w_{255} * n_{255}\} \tag{12}$$

where $w_i = w(i)$. Then Eq. (10) is a linear system with a $256 * 256$ tri-diagonal coefficient matrix. It can be solved efficiently. It should be pointed out that an alternative approach to estimate the local iTMO is through decomposing the HDR image into two layers via the FWLS.

C. HDR Image Estimator

An HDR image can be estimated from the decoded LDR image using the proposed iTMO as shown in Fig. 3. After the decomposition of linearized LDR image which is obtained by gamma correction with the value of gamma as 2, the LDR base layer is expanded with the iTMO function and combined with the LDR detail layer of the decoded LDR image as

$$\hat{Y} = \exp(X_b^{ext} + X_d), \tag{13}$$

where X_b^{ext} is the expanded LDR base layer using the iTMO function and $\hat{Y}$ is the luminance predictor of HDR image. Then the RGB color channels of the HDR image predictor can be computed as

$$\{\hat{R}, \hat{G}, \hat{B}\} = \{R_l, G_l, B_l\} \cdot \frac{\hat{Y}}{Y_l}, \tag{14}$$

where $\{R_l, G_l, B_l\}$ are the color channels of the linearized tone mapped image and Y_l is the corresponding luminance channel.

IV. EXPERIMENTAL RESULTS

We study one global TMO [10] and two local TMOs [11], [14] in this section. The 20 HDR images for the experiments are from the publicly available dataset [24]. The HDR-VDP-2 (version 2.2.1) [25] is employed to evaluate the perceptual quality of the decoded HDR image objectively. The "Q" predictor of the HDR-VDP-2, which ranges from 0 to 100 (100 as the best quality) is consistent with the subjective Mean Opinion Scores (MOS) [26].

We first validate that the proposed two-layer iTMO can recover the HDR image accurately without involvement of coding. In the first step, we validate that the global iTMO function estimation as described in Eq. (5) is useful to inverse tone map the global TMOs. In this experiment, the global TMO [10] is selected and inverse tone mapped using Eq. (5). The inverse tone mapping result is compared with the simple linear expansion, which multiplies linearized tone-mapped LDR image with a constant to approximate the absolute luminance of the LDR image when viewed on an HDR display, as shown in Fig. 4. It is obvious that for all images, the proposed global iTMO estimation outperforms the linear scaling. The local TMO in [14] is selected to evaluate the effectiveness of the proposed two-layer iTMO on local TMOs. In addition to comparing with the linear scaling, the proposed two-layer iTMO is also compared with directly estimating the tone mapping function without the decomposition which corresponds to notation "w/o decomposition" in Fig. 5. The proposed two-layer iTMO is notated as "w/ decomposition" in Fig. 5. As shown in Fig. 5. The iTMO estimation with the two-layer decomposition outperforms the linear expansion while directly estimating the inverse tone mapping function leads to worse perceptual quality. This is because the details of the locally tone-mapped image, which is an additive noise in the global tone mapping function estimation, result in a less accurate mapping function. The average HDR-VDP-Q scores of the linear expansion, local iTMO estimation without decomposition and with decomposition are 61.05, 60.01 and 62.86, respectively.

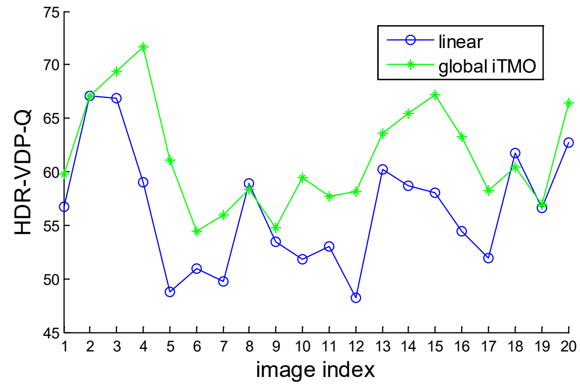

Fig. 4. Inverse tone mapping results for images tone-mapped using the global TMO in [10]. It is obvious that perceptually better HDR estimations are obtained with the proposed global iTMO estimation method.

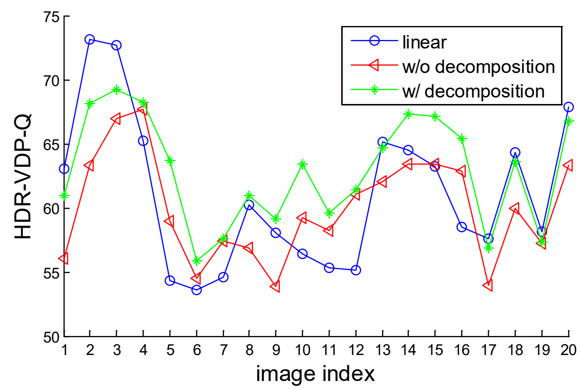

Fig. 5. Inverse tone mapping results for images tone-mapped using the local TMO in [14]. The average HDR-VDP-Q scores of the linear expansion, local iTMO estimation without decomposition and with decomposition are 61.05, 60.01 and 62.86, respectively.

We also verify the efficiency of the proposed scheme by applying it to scalable HDR image coding. In our implementation, we use the JPEG-XT profile A reference software, which is implemented by the Dolby Laboratories Inc, as the base. In their implementation, the residual image which is transmitted in the enhancement layer bitstream is computed as the difference between the HDR image and the decoded LDR image in logarithmic domain. We replace the decoded LDR image with the HDR image estimated from the decoded LDR image using the proposed iTMO when computing such residual image. Three experiments are conducted to verify the effectiveness of HDR image coding via the proposed iTMO.

The first experiment is designed to show that a better compression performance of global tone-mapped HDR image can be achieved with the HDR estimation proposed in Eq. (5). The HDR image is tone mapped with the global TMO in [10]

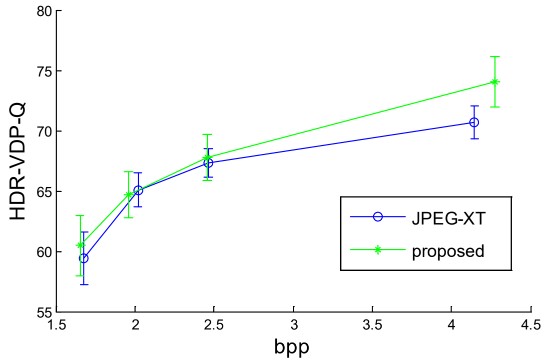

Fig. 6. Mean compression performance of using the proposed global iTMO. All images are tone-mapped with the global TMO in [10]. The quality parameter for the base layer is fixed as 90.

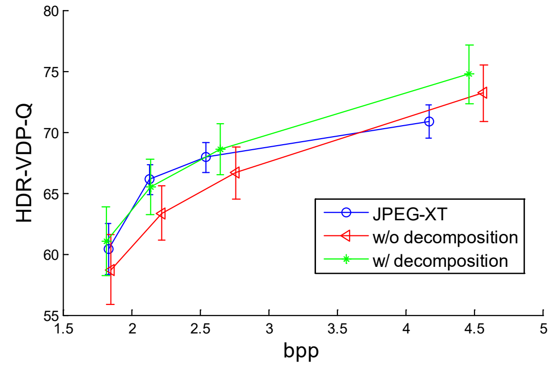

Fig. 8. Mean compression performance of using the proposed local iTMO. All images are tone-mapped with the local TMO in [14]. The quality parameter for the base layer is fixed as 90.

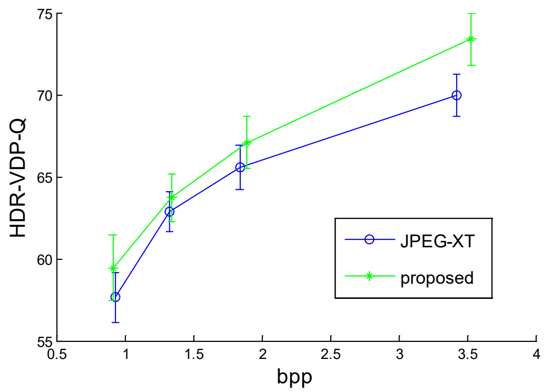

Fig. 7. Mean compression performance of using the proposed global iTMO. All images are tone-mapped with the global TMO in [10]. The quality parameter for the base layer is fixed as 65.

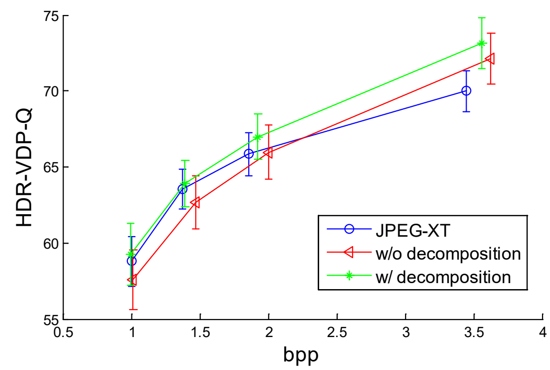

Fig. 9. Mean compression performance of using the proposed local iTMO. All images are tone-mapped with the local TMO in [14]. The quality parameter for the base layer is fixed as 65.

and a corresponding inverse tone mapping function is obtained by solving Eq. (5). With the inverse tone mapping function, a color HDR image is estimated using Eq. (14). In the JPEG-XT framework, the compression parameters q and Q control the quality of base layer and enhancement layer, separately. In our experiments, we test 8 bit rates in total, with q selected as 65 and 90, which corresponds to imperceptible and slightly annoying JPEG compression on base layer, respectively. When q is fixed, Q is selected as $10, 35, 65, 90$ to imitate from heavy to slight compression on enhancement layer. The HDR-VDP-Q scores of these two cases are presented in Fig. 6 and Fig. 7. For each pair of q and Q, the average HDR-VDP-Q score is computed as the arithmetic mean of the HDR-VDP-Q scores of the 20 images. The average bit per pixel (bpp) is computed in a similar manner. Note that the bpp is computed using the toal file size of the base image, the residual image and the meta data, i.e. the iTMO function. The error bar shows the standard variation of the HDR-VDP-Q score. From Fig. 6 and Fig. 7, it can be concluded that with similar bit rate, a perceptually better HDR image can be encoded and decoded via the global iTMO described in Eq. (5).

The second experiment is to show the effectiveness of the two layer local iTMO. In this experiment, the local TMO is designed using the edge-preserving filter in [14] to decompose the luminance of HDR image into two layers and adopting the global TMO in [10] to scale down the base layer. The encoding parameters are selected as the same as the previous experiment. The notation "w/o decomposition" in Figs. 8-11 stands for estimating iTMO function without the decomposition while "w/ decomposition" stands for estimating iTMO function with the decomposition. It can be observed from Figs. 8 and 9 that with a fixed q, the proposed method outperforms JPEG-XT as Q grows. This is because that our iTMO estimates the HDR more accurately, which results in less high frequency information in the residual image. So a smaller Q is needed to compress the enhancement layer.

The third experiment is to show the robustness of the proposed local iTMO. The local TMO in [11] is employed to generate the tone-mapped LDR images with default parameters while the iTMO is designed by using the FWLS as in Section III. The local TMO [11] tries to preserve as much detail as possible so that it is very challenging to model the inverse of this local TMO. The encoding parameters are selected as the same as that in our previous experiments. It can be shown from Fig. 10 and Fig. 11 that though the improvement is not as large as tone mapping with the FWLS, JPEG-XT can benefit from the proposed two-layer local iTMO, especially when a higher perceptual quality of decoded HDR image is required. It should be mentioned that the coding gain could be expected to be increased if the entropy coding is re-designed based on

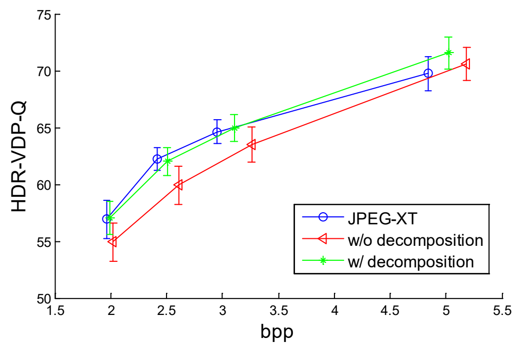

Fig. 10. Mean compression performance of using the proposed local iTMO. All images are tone-mapped with the local TMO in [11]. The quality parameter for the base layer is fixed as 90.

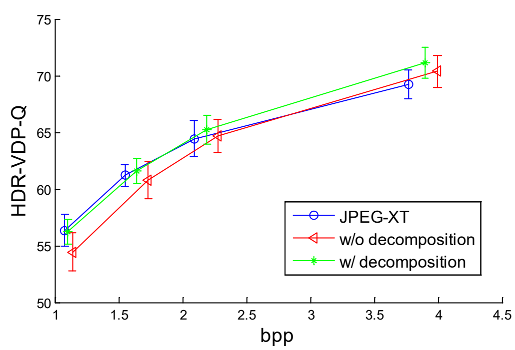

Fig. 11. Mean compression performance of using the proposed local iTMO. All images are tone-mapped with the local TMO in [11]. The quality parameter for the base layer is fixed as 65.

the proposed iTMO. In addition, it can be expected that the proposed method is applicable to the piece-wise linear tone curves in [3]–[5].

V. Conclusion

In this paper, we propose a two-layer local inverse tone mapping scheme by using a fast global edge-preserving smoothing technique. Results show that the proposed two-layer local inverse tone mapping can estimate HDR more accurately. Because of the efficient decomposition and global iTMO function estimation, the proposed local iTMO is also very fast and therefore it is possible to use local TMO and iTMO to develop a scalable coding scheme for HDR images. Our preliminary investigation shows that the proposed iTMO can be adopted to improve the coding efficiency of scalable HDR image coding. How to develop more sophisticated scalable HDR image and video coding schemes using edge-preserving smoothing techniques is an interesting topic for future investigation.

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