INTELLIGENT DETAIL ENHANCEMENT FOR DIFFERENTLY EXPOSED IMAGES

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ABSTRACT

Multi-scale exposure fusion is a fast approach to fuse several differently exposed images captured at the same high dynamic range (H-DR) scene into a high quality low dynamic range (LDR) image. The fused image is expected to include all details of the input images, however, the details in the brightest and darkest regions are usually not preserved well. Adding details that are extracted from the input images to the fused image is an efficient approach to overcome the problem. In this paper, a fast selectively detail enhancement algorithm is proposed to extract the details in the brightest and darkest regions of the HDR scene and add the extracted details to the fused image. Experimental results show that the proposed algorithm can enhance the details of the fused image much faster than the existing algorithms with comparable or even better visual quality.

Index Terms— Exposure fusion, detail enhancement, gradient domain guided image filter, high dynamic range

1. INTRODUCTION

Natural scenes usually have larger dynamic range than the dynamic range of the capacity that a regular camera can capture with a single shot. As a result, details in the brightest and darkest regions of a high dynamic range (HDR) scene may not be recorded. Taking several differently exposed image of the same HDR scene and fusing them together into a high quality low dynamic range (LDR) image is a solution to this challenge [1]. With an exposure fusion algorithm, the multiple differently exposed images are fused to a high quality LDR image directly without generating an intermediate HDR image [2]. Exposure fusion algorithms are usually faster than the tone mapping based approaches [3, 4, 5], especially for mobile devices. However, the details in the fused image are usually not as good as the tone mapped image obtained by tone mapping based approaches. Lots of exposure fusion algorithms [6], [7], [8] were proposed to address the problem. Unfortunately, they cannot preserve all the details of the HDR scene well.

Enhancing details of the fused image is a possible solution to improve the quality of the fused images. However, certain details of the differently exposed images have already been lost in the fusion procedure. Enhancing the details of the fused image can not recover the lost details[10]. This implies that the details should be extracted from the input images directly. On the other hand, it is time consuming to extract details of each input image independently. An interesting idea was proposed in [9] to solve such a problem. The details of all the input images are extracted from a vector filed which is generated from the input images and then a detail layer is obtained by solving a weighted least square (WLS) optimization problem. This detail layer contains almost all the details in all the input images. This approach can indeed enhance the details of the fused image. However, although only one optimization problem need to be solved in the algorithm in [9], the algorithm is slow, especially for large images. At the same time, the details in the brightest and darkest regions are not preserved well. It is desired to develop a simpler detail enhancement algorithm for differently exposed images.

A novel detail enhancement algorithm is introduced in this paper by using features of the darkest and brightest images of an HDR scene. The existing multi-scale exposure fusion algorithms can preserve most details of HDR scenes well except those details in the brightest and darkest regions of the HDR scenes. It is worth noting that the details in the brightest regions of the fused image are mostly from the darkest input image, and the details in the darkest regions are mostly from the brightest image. The quality of fused image can be improved by extracting the details of the brightest regions in the darkest image and the darkest regions in the brightest image and adding to the fused image. Based on this observation, an intelligent detail enhancement method is proposed in this paper. An improved gradient domain guided image filter is proposed to extract the details of the brightest regions in the darkest input image and the darkest regions in the brightest input image with high speed and high efficiency. Then the extracted details are added to the fused image produced by the exposure fusion algorithm in [1]. Experimental results show that the final resultant image indeed has more details than the fused image, especially in the brightest and darkest regions. The proposed detail enhancement algorithm is also much faster than that in [9]. In addition, the proposed algorithm intends to enhance those details lost by the algorithm in [1]. Thus, the visual quality of the enhanced images by the proposed algorithm is better than that of the enhanced images by the algorithm in [9].

The remainder of this paper is organized as follows. In the next section, related works on exposure fusion detail enhancement algorithms and edge-preserving smoothing techniques are provided. An improved GGIF is introduced in the section 3. The improved G-GIF is adopted to design an detail enhancement algorithm for the multi-scale exposure fusion in section 4, followed by the experimental results of the proposed algorithm with comparison to several other state-of-the-art schemes in Section 5. Finally Section 6 concludes this paper.

2. RELATED WORKS

Lots of exposure fusion algorithms [1], [6], [7], [8] were proposed recently. In a subjective user study about exposure fusion algorithms

This work has been supported by National Nature Science Foundation of China under the research project 61620106012, 61573048 and by the International Scientific and Technological Cooperation Projects of China under Grant No.2015DFG12650.

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in [13], it was found that no single state-of-the-art exposure fusion algorithm outperforms the others for all test images. The algorithm in [1] ranks first on average. The algorithm in [1] is a multi-scale based approach, the Gaussian pyramids of the weight maps computed by considering the contrast, saturation and well-exposedness are constructed and the Laplacian pyramids of the differently exposed images are also construed. The decomposed input image and their corresponding weights are multiplied and summed together. The final fused image is obtained by reconstructing the obtained Laplacaian pyramid. An edge-preserving pyramid based exposure fusion algorithm was proposed in [14], it can produce images with more details than the existing exposure fusion algorithms, however, the details in the fusion image could be further improved.

The idea of detail enhancement for exposure fusion image was firstly proposed in [9]. A gradient vector is generated for each input image by considering the exposure quality of each pixel. Then the weighted average of all the gradient vectors is obtained by considering all the gradient vectors of all the input images. Next, an improved optimization problem of the weighted least square optimization problem in [12] is used to extract a detail layer from the gradient vector. Finally, the details are added to the fused image generated by [1] to get the final detail enhanced exposure fusion image. After that, several similar algorithms have been proposed successively. In [15], a new detail abstracting algorithm based on the L_0 norm gradient minimization problem in [16] was proposed. In [17], another algorithm was proposed based on bilateral filter in [18] and it was extended to deal with dynamic scene which have moving objects in the scene in [19]. All the existing algorithms are based on detail extraction from the vector fields generated from all the input images.

The detail extracting algorithms used in the above algorithms are all based on edge-preserving image decomposition algorithms. Besides the algorithm in [18] and [12], a guided image filter (GIF) was proposed in [20]. The GIF is based on a local linear model and the filter is both effective and efficient in lots of applications. The GIF has better performance near edges than the widely used bilateral filter in [18]. However, it may cause halo artifacts near some edges in the detail enhanced images. In [21], a weighted guided image filter (WGIF) was proposed by introducing an edge-aware weighting. In [11], the WGIF is further improved by introducing a gradient domain constraint. The gradient domain guided image filter (GGIF) has better performance near edges than both the GIF and the WGIF. Inspired by the GGIF in [11], an improved GGIF is proposed in the next section, the proposed filter can extract partial of the details according to a gradient targeting image.

3. AN IMPROVED GGIF

Let $I(p)$ be an image to be smoothed. The smoothed image is defined as [20, 21, 11]

$$\hat{I}(p) = a_{p'} I(p) + b_{p'} \; ; \; p \in \Omega_\zeta(p'), \tag{1}$$

where $\Omega_\zeta(p')$ is a square window centered at a pixel p' of a radius ζ, $a_{p'}$ and $b_{p'}$ are two constants in the window $\Omega_\zeta(p')$.

The cost function of the proposed filter is defined as

$$E(p) = \sum_{p \in \Omega_\zeta(p')} [((a_{p'} - 1)I(p) + b_{p'})^2 + \lambda(a_{p'} - \gamma_{p'})^2], \tag{2}$$

where λ is a regularization parameter penalizing large $a_{p'}$. $\gamma_{p'}(\in [0, 1])$ is the target of $a_{p'}$, and it controls the ratio of gradient in the output and input images. Clearly, compared with the GGIF in [11], a new target for $a_{p'}$ is introduced in the improved GGIF.

The optimal values of $a_{p'}$ and $b_{p'}$ are obtained by minimizing the cost function in (2) and their values are computed as

$$a_{p'} = \frac{\sigma_I^2(p') + \lambda \cdot \gamma_{p'}}{\sigma_I^2(p') + \lambda}, \tag{3}$$

$$b_{p'} = (1 - a_{p'})\mu_I(p'), \tag{4}$$

where $\mu_I(p')$ and $\sigma_I^2(p')$ are the mean and variance of pixel p' in $\Omega_\zeta(p')$, respectively.

The smoothed image $\hat{I}(p)$ is finally given as follows:

$$\hat{I}(p) = \bar{a}_p I(p) + \bar{b}_p, \tag{5}$$

where $\bar{a}_p$ and $\bar{b}_p$ are the mean values of $a_{p'}$ and $b_{p'}$ in the window $\Omega_\zeta(p)$, respectively.

Consider the case that the values of $W_{p'}$ are 1's in the window $\Omega_\zeta(p)$. It can be easily shown that

$$\bar{a}_p = 1, \tag{6}$$

$$\bar{b}_p = 0, \tag{7}$$

and

$$\hat{I}(p) = I(p). \tag{8}$$

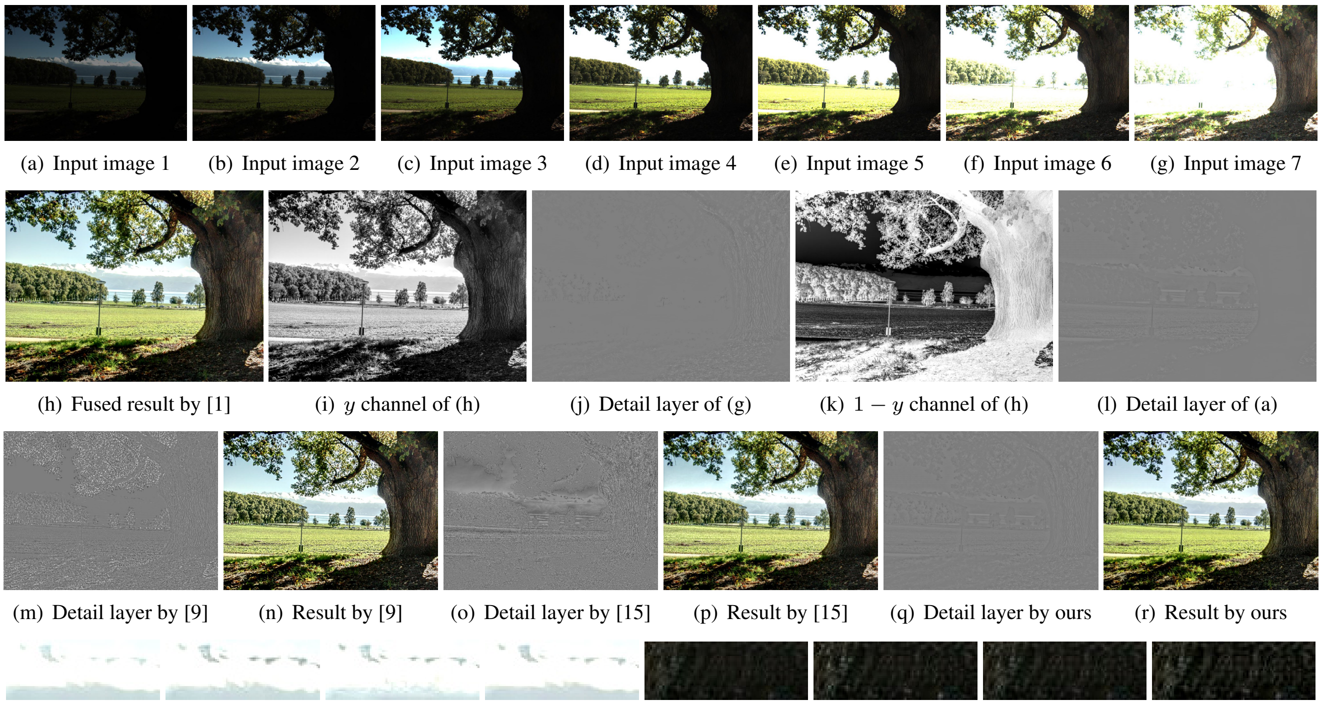
Clearly, no detail is extracted at the pixel p. This implies that the extracted details are determined by the values of $\gamma_{p'}$. In the next section, a novel way is provided for the definition of $\gamma_{p'}$ for the differently exposed images.

4. DETAIL ENHANCEMENT FOR EXPOSURE FUSION VIA THE IMPROVED GGIF

Let the differently exposed images be denoted as I_k, where k is the index of images. Supposing the images are arranged with the luminance of the images, I_1 is the darkest one and I_n is the brightest one. The fused image can be obtained by using the exposure fusion algorithm in [1]. Let the fused image be denoted as R, then R is converted to yuv color space and let R_y be the y channel of R, i.e. the luminance channel of R. The luminance channels of I_1 and I_k are also calculated and denoted as I_1^y and I_k^y, respectively.

As stated in the previous section, the gradient targeting image γ can control the ratio of gradient in the output and input images. In this way, the details of the image can be extracted at different degree. When the image I_n^y is the image to be smoothed, the luminance channel R_y of the fused image R generated by the exposure fusion algorithm in [1] serves as the gradient targeting image. The edge preserving smoothed version $\hat{I_n^y}$ of I_n^y is obtained with the improved GGIF. Then the detail layer D_{dark} of I_n^y is obtained as $(I_n^y - \hat{I_n^y})$. Benefit from the targeting image R_y, only the darkest regions of I_n^y are extracted into the detail layer. As I_n is the brightest input image, the darkest regions in the fused image are exposed best in I_n than any other input images. So it could be assumed that the fine details in the darkest regions of the HDR scene are extracted and included in the detail image D_{dark}. Similarly, when the image I_1^y is the image to be smoothed, the image $(1 - R_y)$ serves as the gradient targeting image. The detail layer D_{bright} of I_1^y is obtained as $(I_n^y - \hat{I_n^y})$. Benefiting from the targeting image $(1 - R_y)$, it could also be assumed that the fine details in the brightest regions of the HDR scene are extracted and included in the image D_{bright}.

Next, all the extracted details are added to the y channel of the



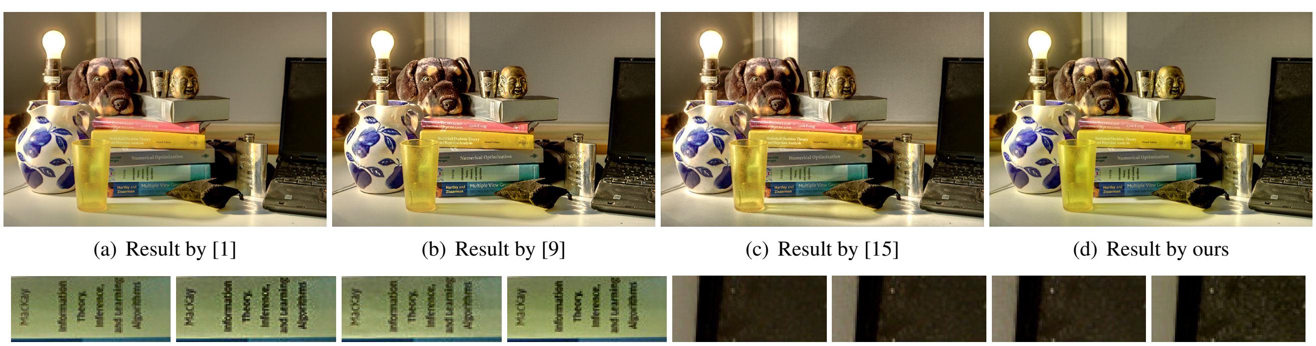
(a) Input image 1 (b) Input image 2 (c) Input image 3 (d) Input image 4 (e) Input image 5 (f) Input image 6 (g) Input image 7

(h) Fused result by [1] (i) y channel of (h) (j) Detail layer of (g) (k) $1-y$ channel of (h) (l) Detail layer of (a)

(m) Detail layer by [9] (n) Result by [9] (o) Detail layer by [15] (p) Result by [15] (q) Detail layer by ours (r) Result by ours

(s) Fig. (h) (t) Fig. (n) (u) Fig. (p) (v) Fig. (r) (w) Fig. (h) (x) Fig. (n) (y) Fig. (p) (z) Fig. (r)

Fig. 1. Comparison of detail enhancement algorithms for exposure fusion with image set 1 "treeunil" .



(a) Result by [1] (b) Result by [9] (c) Result by [15] (d) Result by ours

(e) Fig. (a) (f) Fig. (b) (g) Fig. (c) (h) Fig. (d) (i) Fig. (a) (j) Fig. (b) (k) Fig. (c) (l) Fig. (d)

Fig. 2. Comparison of detail enhancement algorithms for exposure fusion with image set 2 "desk" .

fused image as follows:

$$R'_y = R_y + \theta(D_{bright} + D_{dark}), \tag{9}$$

where θ is constant. In our experiments, the value of θ is 2. In other words, twice of the details are added to the fused image. While the u channel and v channel remain the same as the fused image by [1]. By converting the image from yuv color space to rgb color space, the final detail enhanced image is obtained.

5. EXPERIMENTAL RESULTS

In this section, the detail extraction performance of the proposed gradient domain guided image filter is first evaluated. Readers are invited to view the electronic version of the full-size figures in order to better appreciate the differences among images. In the detail images shown in this paper, the average values of these images are shifted to 0.5 for visualization purposes. One set of images is tested and given in Fig. 1. Fig. 1(a)-(g) are seven differently exposed images. It is seen that Fig. 1(a) has the details in the brightest regions, and Fig. 1(g) has the details in the darkest regions. Fig. 1(h) is the fused image by the exposure fusion algorithm in [1]. It is seen that the details in the brightest and darkest regions are lost in Fig. 1(h). The luminance of Fig. 1(h) is used as a weight image to separate the detail layer of Fig. 1(a). The separated detail layer is shown in Fig. 1(j), it is seen only the details in the brightest regions are separated. Similarly, the detail layer of Fig. 1(g) is obtained and given in Fig. 1(l). From Figs. 1(i)-(l), it can be observed that the proposed filter can be used to extract details of an image according the value of the gradient targeting image.

(a) Result by [1] (b) Result by [9] (c) Result by [15] (d) Result by ours

(e) Result by [1] (f) Result by [9] (g) Result by [15] (h) Result by ours

(i) Fig. (a) (j) Fig. (b) (k) Fig. (c) (l) Fig. (d) (m) Fig. (e) (n) Fig. (f) (o) Fig. (g) (p) Fig. (h)

Fig. 3. Comparison of detail enhancement algorithms for exposure fusion with image set 3 "BelgiumHouse" and set 4 "SevenEleven" .

Then the proposed detail enhancement algorithm is compared with the algorithms in [9] and [15] as well as the exposure fusion algorithm in [1]. From Fig. 1, it is seen that the resultant images of all the three detail enhancement algorithms have more details than the fused images by [1]. From the detail layer obtained by the three different detail enhancement algorithms shown in Figs. 1 (m), (o), (q), it is seen the algorithms in [9] and [15] do not separate the details in the brightest and darkest regions from the details in other regions. As a result, the visual quality of enhanced images is not always improved. The proposed algorithm extracts the details in the brightest and darkest regions and adds them to the fused image by the algorithm in [1]. In other words, the proposed algorithm only enhances details that are lost by the algorithm in [1]. Thus, the visual quality of the enhanced images is improved. Furthermore, apparent halo artifacts could be observed in Figs. 1(p) and (u). Three more sets of images are tested and given in Fig.2 and 3. From Figs. 2(b), (c), (f) and (g), it is seen the algorithm in [9] and [15] may amplify the noises in the image. From all the images in Fig.1-3, a conclusion can be drawn that the proposed algorithm can produce images with better visual quality than the algorithms in [9] and [15].

Table 1. Comparison of Computational Time (second).

Set	Input Image Size	[1]	[9]	[15]	Proposed
1	808*600*7	2.45	+19.96	+36.54	**+0.42**
2	800*532*3	1.04	+17.40	+20.56	**+0.38**
3	1025*769*9	4.66	+38.71	+82.82	**+0.69**
4	2128*1416*5	8.48	+146	+244	**+2.67**

The computational time of each of four algorithms on four test image sets is given in Table 1, evaluated on a laptop with an Intel Core i5-3210 CPU @2.5GHZ and 8GB memory. The computational time of [9],[15] and the proposed algorithm are the computational time of the enhancement procedure. The total computational time can be obtained by adding the corresponding computational time of [1]. All the codes of four algorithms are written in MATLAB without code optimization. From Table 1, it can be found that the proposed detail enhancement algorithm is about 50 times faster than [9] and 100 times faster than [15]. At the same time, the proposed detail enhancement algorithm is faster than that of the algorithm in [1] while the algorithms in [9] and [15] are much slower than the exposure fusion algorithm in [1]. So the entire computation time would be significantly increased if using [9] or [15] as a detail enhancement tool for the exposure fusion algorithm in [1]. It is reported in [20] that the C++ implementation of the GIF takes 40ms/Mp for one color channel while it takes about 200ms/Mp in MATLAB implementation. So it is expected that the proposed GGIF has similar speed and the computation time should be significantly reduced in C++ implementation.

6. CONCLUSION

In this paper, an improved gradient domain guided filter and a detail enhancement algorithm for multi-scale exposure fusion have been proposed. With the proposed filter, the details of an image could be partially extracted according the value of a gradient targeting image. The filter is used to extract the details of the brightest regions in the darkest input image and the details of the darkest regions in the brightest input image. The extracted details are then added to the fused image by an ordinary exposure fusion image. As a result, the final image have more details than the fused image, especially in the brightest and darkest regions. At the same time, the proposed enhancing algorithm runs very fast. It is expectable the proposed algorithm could be adopted to the smart phones to enhance the details of the fused image.

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