Different Levels of Detail Display for Exposure Fusion Using Local Laplacian Filtering

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***Abstract*—Exposure fusion is an efficient method for directly fusing multi-exposure images into a high-quality low dynamic range image, without the high dynamic range (HDR) production and tone mapping process. The previous exposure fusion methods only produced an image that contains a fixed amount of details, which can not satisfy further demands for more detail information. We introduce Local Laplacian Filtering (LLF) for edge-aware image processing to multi-resolution Laplacian pyramid weighted blending method. Our method not only preserves details in the overexposed and underexposed areas, but also shows multi-level detail manipulation by adjusting a simple parameter. Compared with previous methods, our interactive method has a greater flexibility on detail display for the needs of different users.**

***Index Terms*—high dynamic range image, HDR, exposure fusion, Laplacian pyramid, image enhancement**

I. Introduction

The dynamic range of the real world dramatically exceeds the capability of the common image display devices, so a single common image cannot show all the information and details in the bright and dark areas. Besides, the current HDR capture devices [1] [2] [3] are still not popular because of their high prices and hardware requirements. Therefore, we have to capture a stack of different exposed images with a common camera, HDR image is generated by first recovering a HDR radiance map from these images [4] and then making it displayable by tone mapping algorithms [5] [6].

However, the above typical HDR process needs the camera response curve calibration and complicated tone mapping algorithms. So we can directly fuse differently exposed low dynamic range (LDR) images into a well-exposed tone-mapped like image. This strategy is called exposure fusion and it simplifies the HDR pipeline.

Several exposure fusion methods have been proposed in the past decade. Goshtasby [7] proposed a block-based fusion method that selects the block contains the most information by computing the entropy. Raman and Chaudhuri [8] proposed a exposure fusion method with the technique of edge-preserving bilateral filtering. Wei Zhang et al. [9] composed multi-exposure images with the gradient magnitude as the quality measures. The state-of-the-art method was proposed by Mertens et al. [10], which determines the weight map of each image according to contrast, saturation and well-exposedness. On the basis of weight maps, they adopt multi-resolution Laplacian pyramid weighted blending to eliminate seams and halos and achieved perfect results in most cases.

All the methods above produce a certain fusion result with a changeless information and details. However, it is uncertain that the fixed fusion result image is just what we need because it is a difficult problem to judge what result is "best". For example, sometimes we expect as many details as possible, but sometimes we focus more on overall bright and dark effect. Instead of evaluating the quality of HDR image based on complex methodology [12], we propose a new strategy that lets users choose the detail display level as they want freely by adjusting a simple parameter. Our method is based on multi-resolution Laplacian pyramid weighted blending as [10], but we use Local Laplacian Filtering to reconstruct the Laplacian pyramid coefficients, and use a remapping function to manipulate the image detail level controlled by an user parameter. Our method can generate clear and detail-preserving fused result without halos and have a greater flexibility on detail display for the needs of different users.

II. Our Approach

Assume that there are N different exposed input images ($I_1 \cdots I_N$). These input images are all captured by a common camera from a static scene with no moving object or camera motion and have been aligned. Based on the multi-resolution exposure fusion, we use Local Laplacian Filtering (LLF) to construct the Laplacian pyramid coefficient one by one for each input image. The technique of Local Laplacian Filtering was proposed by Paris et al. [13] for edge-aware image processing and has been applied to edge-preserving smoothing, detail enhancement and tone mapping. We combine this technique with multi-resolution exposure fusion to obtain multi-level detail display with a simple parameter adjustment according to different detail demands. Our method is different from common methods of contrast enhancement because we implant the detail manipulation process to the generation of Laplacian pyramid coefficients. The overview pipeline of our approach is showed in Fig. 1.

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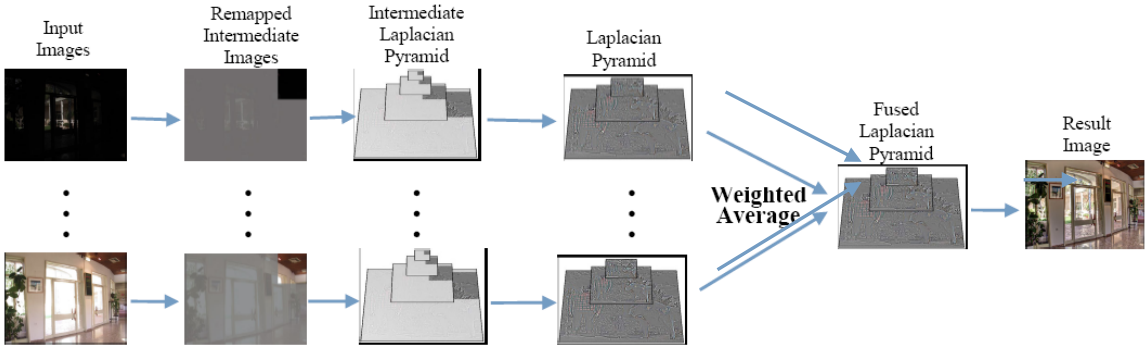

Figure 1. The pipeline of our approach.

A. Build the Laplacian pyramid by Local Laplacian Filtering

For each coefficient, we generate an intermediate image processed locally by a point-wise remapping function $R(I')_{g,\sigma}$, and then compute Laplacian pyramid of the intermediate image, finally copy the corresponding coefficient to the output pyramid by

$$L\{I(k,x,y)\}^d = L\{R(I')_{g,\sigma}(k,x,y)\}^d . \quad (1)$$

where $L\{I(k,x,y)\}^d$ is the Laplacian pyramid of the k-th image on the d-th level. The size of intermediate image I' is $K\times K$, and K is related to the current pyramid level d by $K=2^{d+3}+1$. The meaning of g and σ is explained in the next section.

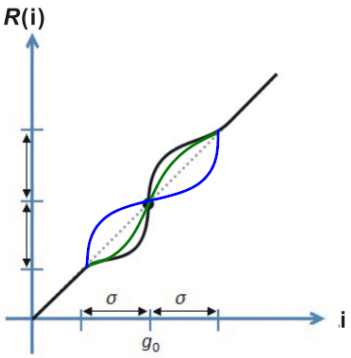

Figure 2. S-shaped function to manipulate details. The value g_0 is the Gaussian pyramid coefficient of the 0-th level and the parameter σ is used to distinguish edges from details. σ=0.05 for black curve, σ=0.5 for green curve, σ=2 for blue curve and σ=1 for dash line.

B. Detail Manipulation by S-shaped Function

The detail manipulation is controlled by the remapping function $R(I')_{g,\sigma}$. For each coefficient (x,y,d) of the k-th image, this remapping function depends on the local image value from the Gaussian pyramid $g = G_0(x,y)$ and the parameter σ is used to distinguish edges from details. Intensity variations smaller than σ should be considered fine-scale details and larger variations are edges. As a center point for this function we use the Gaussian pyramid coefficient of the 0-th level, which represents the image intensity at the location and scale where we compute the output pyramid coefficient. In this paper, we aim to manipulate details and produce multi-level details, so we modify the image fine-scale details only and leave the edges not treated. Therefore, the parameter σ controls what magnitude of variations should be considered edges that are preserved constant. Large values allow the filter to manipulate larger portions of the details and yield larger visual changes.

For the RGB color image in our method, we define details as colors within a ball of radius σ centered at $\mathbf{g}$ and edges as the colors outside it. That is, if $\|\mathbf{i} - \mathbf{g}\| < \sigma$, it is regarded as detail, where $\mathbf{i}$ is a three-dimensional vector for the RGB channels. So, the remapping function is defined as

$$R(\mathbf{i}) = \mathbf{g} + \sigma \frac{\mathbf{i}-\mathbf{g}}{\|\mathbf{i}-\mathbf{g}\|} f\left(\frac{\|\mathbf{i}-\mathbf{g}\|}{\sigma}\right) \quad (2)$$

This smooth mapping function modifies the fine-scale details by altering the amplitude around the vector $\mathbf{g}$. The value σ is set to 0.5 in our method. To modify the details of an image we use an S-shaped power curve function for the local manipulation of image contrast by $f(\Delta)=\Delta^{\alpha}$, where α is a user-defined parameter with the value of $\alpha>0$. When $\alpha>1$, the details are decreased. And when $0<\alpha<1$, the details are increased. As α is smaller, the amplitude of detail increasing is larger (Fig. 2). If users prefer richer and clearer details, they can adjust this parameter closer to 0. When $\alpha=1$, the detail is not modified.

In order to reduce noise and artifacts, we limit the smallest Δ amplified by

$$f(\Delta) = \lambda\Delta^{\alpha} + (1-\lambda)\ \Delta \quad (3)$$

where λ is a smooth step function equal to 0 if Δ is less than 1% of the maximum intensity, 1 if it is more than 2%, with a smooth transition in between.

In its basic form detail manipulation is applied at all scales, but one can also control which scales are affected by limiting processing to a subset of the pyramid levels. The level of Laplacian pyramid controls the frequency of the details that are manipulated. The low level pyramid processes the high frequency information and the high level pyramid processes the low frequency information. We only modify the lower levels of pyramid (0 to 2 levels in this paper) by LLF to manipulate the high frequency details and remain other levels as their original form.

C. Weighted Fusion

After generating the Laplacian pyramid coefficient of each input image, we adopt the multi-resolution exposure fusion method [10] to eliminate seams and halos. This method directly fuses multiple exposure images to a high-quality detail-preserving result without radiometric calibration of camera response function and the exposure setting parameters. This method uses the weighted production of three quality measures including contrast, saturation and well-exposedness as the weight map by

$$W_{x,y,k} = (C_{x,y,k})^{w_C} \times (S_{x,y,k})^{w_S} \times (E_{x,y,k})^{w_E} \quad (4)$$

where w_C, w_S and w_E are corresponding weighting exponents ($w_C = w_S = w_E = 1$ in this paper). Then we build the normalized Gaussian pyramid of each weight map, and obtain the fused Laplacian pyramid for each level separately by

$$L\{F\}^d_{x,y} = \sum_{k=1}^{N} L\{I\}^d_{x,y,k} G\{\hat{W}\}^d_{x,y,k} \quad (5)$$

where $L\{I\}^d_{x,y,k}$ is the Laplacian pyramid of the k-th image on the d-th level, $G\{\hat{W}\}^d_{x,y,k}$ is the normalized Gaussian pyramid of the corresponding weight map $W_{x,y,k}$. Finally, the Laplacian pyramid $L\{F\}^d_{x,y}$ is collapsed to generate the fused image F.

III. Experiment Results

All of our method results are computed on a 2.33GHz Intel core 2 Duo CPU, 1.96 GB memory. We have done large number of experiments to prove the effectiveness of our method. For example, Fig. 3 shows three groups of different exposed HDR scenes. In each scene, we show 4 different fusion results of different parameter setting. Our method not only preserves the details of bright and dark areas, but also can generate different levels of detail manipulation results by adjusting the user-defined parameter α. When the parameter α becomes smaller to 0, the details and the fine information are more visible, and the definition of the result image is higher as α changes, such as the drawing boards on the wall (Fig. 3(a)), details on the ground (Fig. 3(b)), cloud and grass (Fig. 3(c)). So our method has advantage over previous exposure fusion

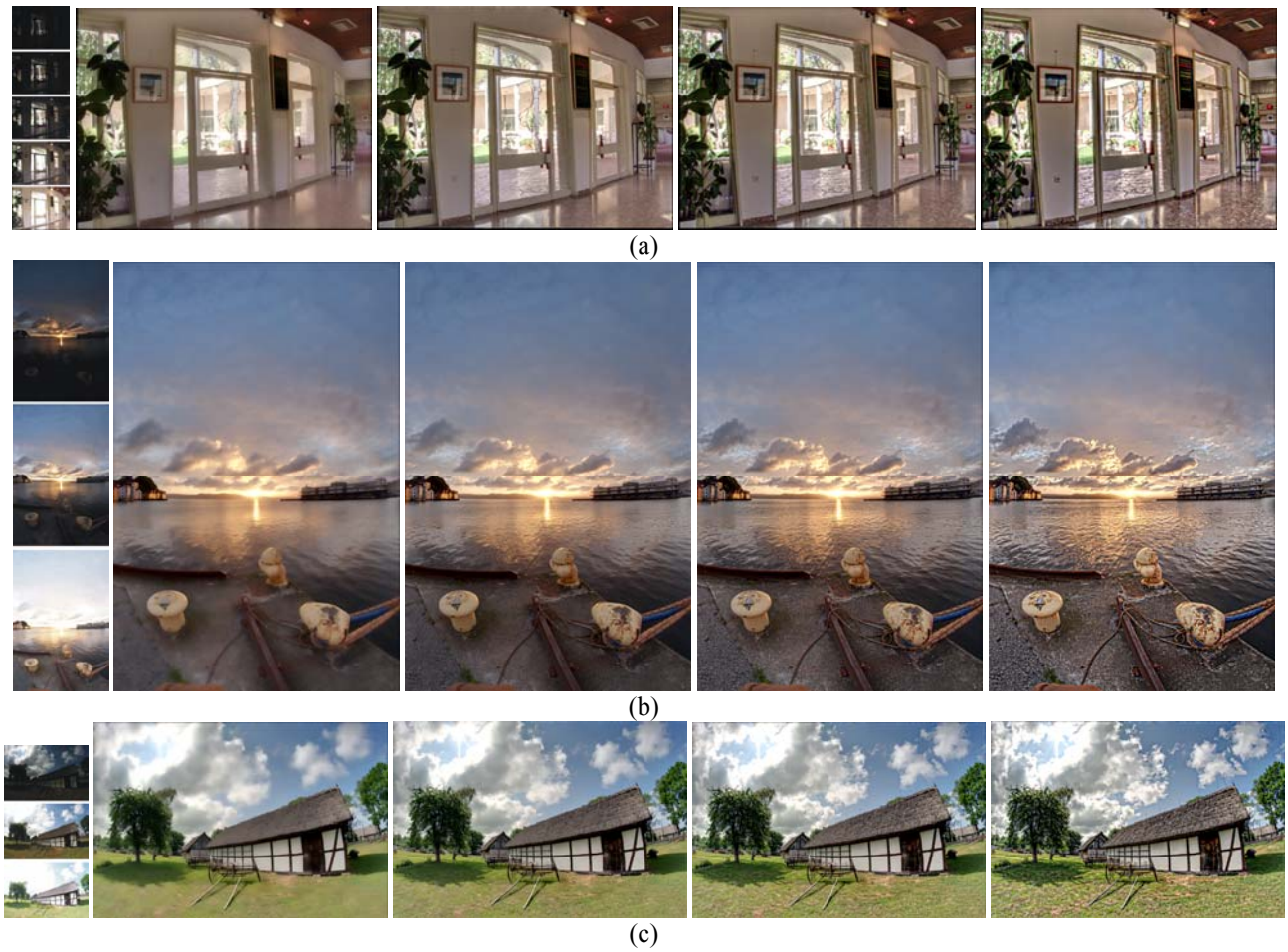

Figure 2. (a), (b), (c) are three groups of different exposed scenes. In each group, we show four different fusion results of different parameters. From left to right: α=2, α=1, α=0.5, α=0.05.

methods for greater flexibility and detail diversity. We adopt the average gradient to measure the amount of details diversity. The average gradient is greater, the more and clearer details the image contains. The average gradient is defined by

$$\nabla\overline{g} = \frac{\sum_{x=1}^{H}\sum_{y=1}^{W}\sqrt{\frac{\nabla_x^2 F(x,y)}{2}+\frac{\nabla_y^2 F(x,y)}{2}}}{H\times W} \tag{6}$$

where H and W are the image height and width, respectively. $\nabla_x^2 F(x,y)$ and $\nabla_y^2 F(x,y)$ are the average horizontal and vertical derivatives of (x, y), respectively. TABLEI shows the average gradient of different α for the fused images in our paper. We can see that the average gradient becomes larger when α changes smaller, which prove the theory of our approach by quantitative analysis. More fusion results are showed in Fig. 4.

Our algorithm is implemented easily without camera calibration and tone mapping operations. It takes less than one minute to fuse three exposures with resolution of 1 megapixel using single thread.

TABLE I.
AVERAGE GRADIENT VARIATION OF DIFFERENT PARAMETERS

Fused images	Average gradient of different α			
	α=2	α=1	α=0.5	α=0.05
Fig. 3(a)	1.767	2.531	3.408	5.108
Fig. 3(b)	0.711	1.184	1.953	3.157
Fig. 3(c)	1.817	2.891	4.230	6.285

IV. CONCLUSION AND FUTURE WORK

In this paper, we extend the traditional exposure fusion method to a more flexible and adjustable version. We adopt Local Laplacian Filtering to generate an remapped intermediate image and rebuild the low levels of Laplacian pyramid coefficients. The remapping function is an S-shaped power curve function controlled by a simple user parameter to manipulate details of different levels. Our method not only preserves the overexposed and underexposed details of the whole scene without halos, but also has a greater flexibility and interactivity because users can get their desired fused image by adjusting the parameter easily.

We would like to achieve the real-time fusion process with GPU implementation or a multi-core architecture in the future work to improve the efficiency because our algorithm is highly data parallel. We also want to design other functions to manipulate Laplacian pyramid coefficients from more aspects besides the image details because users not just pay attention to the image details. For example, the richness of colors, the bright and dark visual effects and so on. We plan to provide more parameters to give users more freely to customize their desired fusion type.

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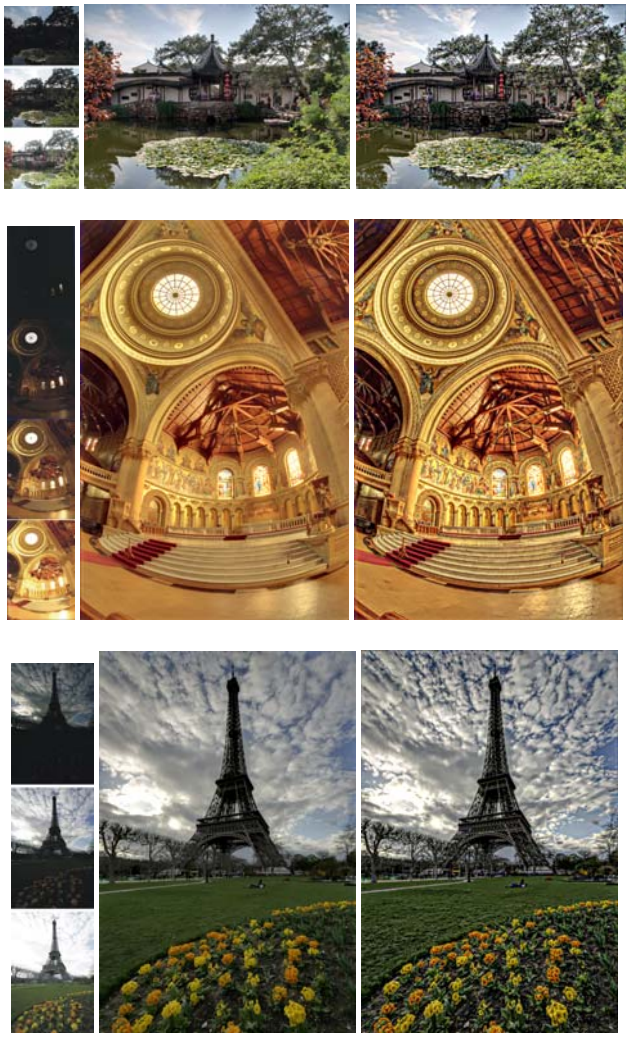

Figure 3. More fusion results with different parameter setting (α=1 for the left image and α=0.05 for the right image).

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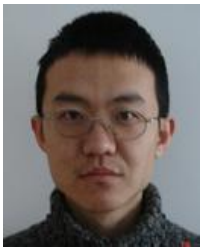

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