Fast Exposure Fusion Based on Camera Response Function

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ABSTRACT

This paper proposed a fast multi exposure images fusion algorithm based on the camera response function for high dynamic range scene imaging, which greatly improve the efficiency and ensure the good quality of the fused image. The algorithm calibrated the camera response function in advance, and then calculated the mapping curve between the scene illuminance and pixel value according to the exposure time. When fuse multi-exposure images, the mapping curves of the images are connected to obtain a new mapping curve which can curve the whole luminance range. Then the fused image can be obtained through the new mapping curve. The experimental results demonstrate the good effectiveness and high efficiency of proposed algorithm.

KEYWORDS

Exposure Fusion, Response Function, High Dynamic Range, Illuminance Curve.

INTRODUCTION

The illuminance range of the realistic scene changes from 10-3 cd/m2 to 105cd/m2, reaching tens of millions, so is called high dynamic range (HDR) scene. But the dynamic range of the digital camera is 0 to 255, which is much less than
that of the realistic scene, so is called low dynamic range (LDR). Because of the limiting dynamic range, there will be under- or over- exposed regions in the taken for the HDR scene. In order to imaging HDR scene, researchers proposed to fuse multi-exposured images to obtained a well-exposed image. There are mainly two kinds of HDR imaging methods through multi-exposured images. One kind of them choose the well exposured regions from the multi-exposured images by certain quality evaluation metric and fuse them in image domain directly, which is image domain fusion method. Mertens[1] used the well-exposedness, contrast and saturation as the evaluation metric, which is decomposed as Laplacian pyramid to fuse with multi-exposure image in different scales. Shutao[2] used a recursive filter to refine the weight map structured by well-exposedness and saturation. The gradient amplitude was used to fuse the multi-exposure images by Wei[3]. Shen[4] used the generalized random walk model to refine the fusion weight. All the fusion methods in image domain don’t take advantage of the information on exposure time and imaging system. But in most practical applications, we can conveniently set the exposure time by program to obtain the multi-exposed image sequence. Therefore, we can make full use of the imaging system prior information to improve the effectiveness and efficiency in fusing multi-exposured images.

The other kind methods fuse the images in the radiance domain based on the camera response function. The pixel value of input images is mapped into luminance domain through the response function to get the illuminance map, which is HDR image. Robertson[5] considered the imaging noise and the error introduced by the discrete characteristic of the pixel value. The maximum likelihood estimation method is used to get the relationship between illuminance and light exposure, where the light exposure can be obtained by response function. Thus, the illuminance map is calculated through the camera response function. Neve[6] combined the computing of camera response function and illuminance image together to optimize the recovering response function by Debevec[7] to improve the quality of the illuminance image. Nayar[8] proposed a method which needs no prior information of the exposure time and response function. The polynomial curve fitting method was used to calculate the camera response function with ratio of light exposure for multi-exposured images iteratively. Then the ratio of light exposure and polynomial curve can be obtained together when convergence.

The existing exposure fusion algorithm based on the camera response function is almost in the radiometric domain. The main problem of radiometric domain fusion algorithm is that it cannot generate LDR image directly. The HDR image needs to be processed by tone mapping, which reduces the computation efficiency of the algorithm. And the quality of the LDR image is greatly related to the corresponding tone mapping algorithm.
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Camera Response Function and Illuminance Curve

The camera response curve maps the light exposure to the image gray. The response function is defined as:

\[ I = f(E) \]  \hspace{1cm} (1)

Here, \( I \) donates the pixel value, and \( E \) represents the light exposure. If only change the exposure time, the light exposure is proportional to the exposure time \( \Delta t \) and scene illuminance \( Z \).

\[ E = Z \cdot \Delta t \]  \hspace{1cm} (2)

Debevec[7] use a set of multi-exposed images with different exposure time of the same scene to calculate the camera response function. The value of the ith pixel in the image with the exposure time \( \Delta t_j \) is:

\[ I_{ij} = f(Z, \Delta t_j) \]  \hspace{1cm} (3)

Because the response curve is continuous and monotonous, the function f is reversible.

\[ g(I_{ij}) = \ln Z_i \cdot \ln \Delta t_j \]  \hspace{1cm} (4)

Here, \( g(I_{ij}) = \ln f^{-1}(I_{ij}) \). \( N \) pixels are selected in the \( P \) different exposed images for the same scene, then the following optimization formula can be obtained.
The second-order differential term in (5) is used to ensure that the calculated response curve is smooth. $\lambda$ is the weight of the smooth term, the larger value of $\lambda$ the smoother response curve can be obtained. Because the pixel value $I$ is discrete, so the second-order differential term can be calculated as following:

$$\dot{g}(I) = g(I-1) + g(I+1) - 2g(I)$$  \hspace{1cm} (6)

In order to solve the optimization equation of formula (5), the unit light exposure is set to correspond to intermediate gray value:

$$g(I_{mid}) = 0 \quad I_{mid} = \frac{1}{2}(I_{max} + I_{min})$$  \hspace{1cm} (7)

Her up to now, $g(\cdot)$ and $\ln(Z_i)$ are unknown in formula (5), it can be reduced to a linear least square problem, which can be solved by the single value decomposition (SVD).

Through adjusting the exposure time, we can get a set of multi-exposed images with different mapping curve, as shown in Figure 1.

![Figure 1. The illuminance curves of multi exposure time (t_1 > t_2 > t_3).](image)
The image will lose the dark area information of the scene when the exposure time is short, such as the mapping curve of \( t_3 \) in Figure 1. On the other hand, the information of the bright area will be lost when the exposure time is too long, as the mapping curve of \( t_1 \) in Figure 1. The image will lose dark and bright areas at the same time for the HDR scene when the exposure time is set the intermediate value, the mapping curve is shown as the \( t_2 \) in Figure 1. Therefore, the single exposure cannot cover all the range of the illuminance for the HDR scene. However, the entire illuminance of the HDR scene can be covered by a set of different exposures. By selecting and combining the best segments of the mapping curves of different exposure time, we can obtain a new mapping curve which can cover the whole illuminance range. At the same time, the fused image can be obtained according to the compositing mapping curve.

**Multi Exposure Fusion via Fusing Illuminance Curve**

From the above analysis, we can obtain multiple overlapping illuminance curves covering a larger illuminance range by multiple different exposures. According to these illuminance curves, the illuminance information of each pixel in the scene can be obtained. Suppose there is an illumination curve covering the entire illumination range, the illuminance of the scene can be mapped into the pixel, then the fused image can be obtained.

The illuminance curves of two different exposure times are shown in Figure 2. This paper reconstructs an illuminance curve covering a large illuminance range by connecting these two illuminance curves. The left half of the illuminance curve of exposure time \( T_1 \) and the right half of the illuminance curve of \( T_2 \) are selected for the reconstruction.

![Mapping curves of two different exposure times](image)

Figure 2. Mapping curves of two different exposure times (The red for exposure time \( T_1 \), the blue for \( T_2 \), and \( T_1 > T_2 \)).
The midpoint of the luminance coincidence area is selected as the abscissa of the connection point.

\[
\ln(Z_m) = \frac{\ln(Z_{1\max}) + \ln(Z_{2\max})}{2}
\]  \hspace{1cm} (8)

Then, the pixel value \( I_{1m} \) and \( I_{2m} \) can be obtained on the two curves corresponding to the \( Z_m \). The ordinate of \( M \) is set as the mean of these two values.

\[
I_M = \frac{I_{1m} + I_{2m}}{2}
\]  \hspace{1cm} (9)

In order to ensure that the dynamic range of the illumination curve remains unchanged before and after fusion, the two endpoints of the reconstructed illumination curve are set as the sum of the two ends of the original illumination curve. At the same time, the reconstructed illumination curve should be consistent with the shape of the original illumination curve as far as possible. In this paper, the gradient is used to represent the shape of the illumination curve, that is, the reconstructed illumination curve should have a similar gradient value to the original illumination curve in each interval.

Because the range of illumination curve is discrete, the inverse function of illumination curve is calculated in this paper. According to the gradient of the inverse function and the inverse function, the optimization formula of the inverse function of the left half illuminance curve can be obtained as follows.

\[
\min_{g} \int_{I_o}^{I_M} (G'(I) - g'_1(I))^2 \, dI \hspace{0.5cm} G(I_o) = Z_o, G(I_M) = Z_M
\]  \hspace{1cm} (10)

Here, \( G(I) \) and \( g_1(I) \) represent the inverse functions of the reconstructed illumination curve and the original illumination curve of \( T_1 \) respectively. \( G'(I) \) And \( g'_1(I) \) represents the first derivative with respect to the gray value.
We can get the following equation by solving (11):

\[ G''(I) = g''_1(I), \quad I \in (I_O, I_M), G(I_o) = Z_o, G(I_M) = Z_M \]  \hspace{1cm} (11)

Here \( G''(I) \) and \( g''_1(I) \) represent the second derivative with respect to the gray value.

The equation (11) is the standard two-point boundary value problem. Because the function \( G(I) \) is discrete, the equation (11) can be solved through the numerical methods for differential equations.

In the same way, the right half of the reconstructed illuminance curve can be calculated.

After the illumination curve covering the whole scene is reconstructed, the fused image can be obtained by the re-projection. Firstly, the illumination value of the pixel is obtained according to the pixel value and illumination curve of the current image, and then the grayscale value of the current pixel is obtained by rebuilding the illumination curve.

The calculation method of fusion image is shown below.

\[
I_{F,P} = \begin{cases} 
F(g_1(I_{1,P})) & I_{1,P} \in [I_O, I_M] \& I_{2,P} \notin (I_M, I_P) \\
F(g_2(I_{2,P})) & I_{1,P} \notin [I_O, I_M] \& I_{2,P} \in (I_M, I_P)
\end{cases}
\]  \hspace{1cm} (12)

Theoretically, the gray value of the image has only the above two possibilities, but in practice, affected by noise and illumination curve error, pixels that do not belong to the above two situations can exist. For the exceptional cases, this paper deals with them in the following ways:
\[
I_{F,p} = \begin{cases} 
\frac{1}{2} \left( F\left( g_1(I_{1,p}) \right) + F\left( g_2(I_{2,p}) \right) \right) & I_{1,p} \in [I_0, I_M] \& I_{2,p} \in (I_M, I_p] \\
F\left( g_1(I_{1,p}) \right) & \left| I_{1,p} - I_{1m} \right| \leq \left| I_{2,p} - I_{2m} \right|, I_{1,p} \notin [I_0, I_M] \& I_{2,p} \notin (I_M, I_p] \\
F\left( g_2(I_{2,p}) \right) & \left| I_{1,p} - I_{1m} \right| > \left| I_{2,p} - I_{2m} \right|, I_{1,p} \notin [I_0, I_M] \& I_{2,p} \notin (I_M, I_p] 
\end{cases}
\] (13)

Through the above calculation process, two grayscale images can be fused directly, but for color images, which are converted to YUV color space as the fusion method in[9]. The color difference channel U and V are fused by saturation, and the luminance channel Y is fused by the proposed algorithm.

**EXPERIMENTS AND ANALYSIS**

In order to evaluate the proposed fusion algorithm, we conducted two experiments to compare the proposed method with classical algorithms [1,2,3]. The first group of multi-exposed images were taken from the public data set, and the second set of images were taken by our own camera.

The multi-exposed images from the public data set is used to calibrated the response function. Then, we choose the two images from the original sequence to fuse, as shown in Figure 3(a). It can be seen that the fusion result by proposed method does not lose the details in the original image. And the effect of the proposed algorithm is comparable to other methods.

![Figure 3. The multi-exposed images and the fused images of different methods.](image_url)
Through changing the exposure time of the camera, we get a sequence of images with different exposure for the same scene to calculate the camera response function. In the process of photographing, the camera didn’t shift, and the scene didn’t change. Other imaging parameters of the camera remained unchanged. We used the camera to photograph a HDR scenes and two different exposure time are used to capture the multi-exposured images, which are shown in Figure 4.

![Multi-exposured images](image1)

Figure 4. The photographed multi-exposured images.

The fused results of the multi-exposured images in Fig. 4 are shown in Figure 5. As shown in Figure 5, the fused result of proposed method can preserve the well exposed regions of the original images. Due to the large brightness difference between the two original images in the second row in Fig. 4, the fused image by Shutao[2] has obvious halo. The building outside the window isn’t clear in the fused image by Mertens[1], see Figure 5(b). Because of considering the exposure information of the original multi-exposured images, the proposed algorithm can adapt to the large difference in the brightness of the multi exposure images.

![Fused images](image2)

(a) Shutao [2]  (b) Mertens [1]  (c) Proposed method

Figure 5. The fused images of the second-row images in Figure 4.
We compared the computational efficiency of the proposed algorithm with the methods[1,2]. The method[3] provided the executable program, which is difficult to measure running time and cannot process large images. All algorithms are implemented by MATLAB. The configuration of the running platform is i5-6200U CPU with 2.30 GHz, and the memory is 8.00 GB in Windows 10. The running time of different algorithms is shown in Table 1. It illustrates that the proposed method reached almost 4 FPS for the resolution of 768×512. The running time of Shutao[2] increases rapidly with the image size. The proposed fusion method is approximately proportional to the size of the image. And the multi-exposed images are fused in pixel value range in the proposed method, which is beneficial to parallel processing, so that the computational efficiency of the proposed algorithm has great space to improve.

TABLE I. THE COMPUTATIONAL EFFICIENCY OF DIFFERENT ALGORITHMS (SECONDS).

| Multi-Exposed Images | Shutao[2] | Mertens[1] | Proposed method |
|----------------------|-----------|------------|-----------------|
| 768×512× 2           | 1.32      | 1.48       | 0.28            |
| 780×1052× 2          | 2.08      | 2.24       | 0.48            |
| 1560×2104× 2         | 8.21      | 7.54       | 1.85            |

CONCLUSION

This paper proposed a fast multi-exposed images fusion method for HDR imaging based on the camera response function. Compared with the existing fusion methods, it is proved that the fusion method proposed in this paper can not only guarantee the effect of the fused image, but also have better robustness, and the computation efficiency is much higher than some existing fusion algorithms. Although two different multi-exposed images is used in this paper, the algorithm is easily generalized to more multi-exposed images.

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