Colorful Multi-Exposure Fusion with Guided Filtering based Fusion Method

*Changho Song, Soowoong Jeong, and Sangkeun Lee**

Graduate School of Advanced imaging Science, Multimedia, and Film, Chung-Ang University / Seoul, South Korea
**Corresponding Author (sangkny@cau.ac.kr)*

Abstract: Multi-exposure fusion(MEF) are techniques to obtain the high dynamic range. One of MEF methods, guided filtering-based fusion(GFF) has good performance for preserving details of original images. However, GFF method considers only details, which causes a problem of missing color information. To solve this problem, we proposed a saliency map-based approach for considering both detail and color information. The experimental results show that the proposed method can provide better color quality than the existing methods.

Keywords: High dynamic range image, Multi-exposure fusion, Guided filtering, Color image quality index.

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1. Introduction

The human visual system has no difficulty in perceiving dynamic scene information even if their exit dark and bright areas of the same scene, but digital device has limitation to capture the whole scene. For example, a digital image is often insufficient to provide all information in a scene due to dark areas (by under-exposure) or bright areas (by over-exposure). The reason why this happen that the dynamic range of digital device is narrower than that of the human visual system.

High dynamic range (HDR) techniques have been studied to overcome the gap of dynamic range between human visual system and digital device [1]. Unfortunately, despite many studies, there have been some problems such as halo artifact, color distortion, saturation, etc.

The purpose of HDR techniques is to make digital images look like those perceived by human eyes. Moreover, HDR image can provide more information about the general digital image, and can be used pre-processing algorithm for, such as a detection, recognition to increase performance [2].

HDR techniques can be categorized into two methods, high dynamic range imaging(HDRI) and Multi-exposure fusion(MEF). HDRI is an algorithm for obtaining HDR image by combining multi-exposure image. HDR image is cannot be expressed in general digital display because it has 32-bit floating point numbers to represent each of the channels. Therefore, it is common to use tone mapping method for converting HDR image into a Low dynamic range (LDR) image [3]. MEF is also using multi-exposure images. However, compared HDRI, the implementation process is relatively simple, as it does not generate HDR image and immediately fuse the multi-exposure image into HDR-like, LDR image [3]. For these advantage, we applied MEF method.

We start with a discussion of related work in Section 2. And, one of previous study, Guided Filtering based Fusion(GFF) method [4] is presented in Section 3. After that, we present our approach for colorful MEF method in Section 4. The experimental results is presented in Section 5. Finally, we draw our conclusions in Section 6.

2. Related work

Kóczy proposed Gradient based Fusion(GF) method [2]. GF method measure details with gradient each color channel and construct non-overlap block based weighting map. However, because of differently weight value for each color, it is possible to distort the colors of the original colors. Mertens proposed Laplacian Pyramid based fusion(LPF) method [3]. LPF method constructs Laplacian pyramid and Gaussian pyramid considering contrast, color saturation, well-exposedness. This method has the advantage of reducing the halo effect of multi-resolution method, but some detail is not preserved. Shen proposed Generalized Random Walks based Fusion(GRWF) method [1]. GRWF method constructs weighting map considering the local contrast and color consistency and optimize it using the generalized random walk model. Although this method is relatively fast, it tends to miss local details. Shutao Li proposed Recursive Filter based Fusion(RFF) method [5]. RFF method measure detail with Laplacian and blend using a recursive filter. Pixel based weighting maps have the advantage of preserving details, but there are disadvantages to noise. Shutao Li proposed Guided Filtering based Fusion(GFF) method [4]. GFF method measure details with Laplacian and blend using guided filter [6]. In the blending process, input images are decomposed by high frequency layer and low frequency layer. And each of the layers is blended according to frequency characteristics.

The important point of MEF method is that details must be exactly measured from original images, and the details should not be missed during the blending. Focusing on these points, we adopted GFF method.

The flowchart of the proposed method is presented in Figure. 1. The saliency maps are calculated from multi-exposure image, and weighting maps are constructed with it. To blend for according to frequency characteristics, multi-exposure image are decomposed, and each of the layers is weighted sum using referred weighting maps. GFF method calculated pixel based saliency maps, and used edge preserving filter to preserve detail from original images. But, it has problem that color information is not preserved. To solve this problem, we employed simple color measure for saliency maps.

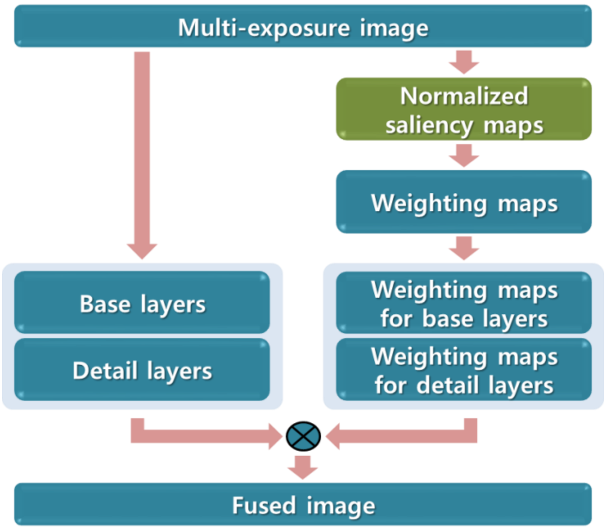

Fig. 1. Flowchart of proposed method.

3. GFF method

A. *Saliency map and Weighting map*

Laplacian filtering is applied to each multi-exposure image to obtain the details

$$S^n = (|I^n * L|) * g \tag{1}$$

where S^n is saliency maps, n is n-th multi-exposure image, I^n is a grayscale image of multi-exposure image, L is Laplacian filter, $|\cdot|$ is absolute operator, * is convolution operator, g is Gaussian filter. Gaussian filter is applied to result of laplacian filtering for reducing noise. Next, the saliency maps are compared to determine the weighting maps as follows.

$$P^n(x,y) = \begin{cases} 1, & \text{if } S^n(x,y) = \max(S^1(x,y), \ldots, S^n(x,y)) \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where P^n is weighting mapsand n is n-th multi-exposure image. In weighting map is determined by saliency maps. If highest saliency, 1, otherwise, 0.

B. *Two scale decomposition and fusion*

The multi-exposure image are decomposed into two-scale layer by average filtering. Low frequency layers(base layers) are obtained from average filtering to each multi-exposure image. And high frequency layers(detail layers) are obtained by difference of multi-exposure image and base layers.

Meanwhile, weighting maps are also decomposed into two-scale weighting map by guided filtering. The weighting maps for detail layers and the weighting maps for base layers is obtained as follows.

$$W_h^n = G_h(P^n, I^n) \tag{3}$$
$$W_l^n = G_l(P^n, I^n) \tag{4}$$

where W_h^n is weighting maps for detail layer, G_h is guided filter that has the characteristics of high frequency. W_l^n is weighting maps for the base layer, G_l is guided filter that has the characteristics of low frequency. And then fused image is obtained by a weighted sum of each of the layers and refinement weighting maps.

4. Proposed method

A. *Refinement of saliency map*

In GFF method, the saliency is calculated by only Laplacian. And this method cause problem of missing color information. To solve this problem, we consider not only detail saliency but also color saliency. The detail saliency is obtained by Laplacian filter and the color saliency is obtained by simple color measure that distance of each of colors and color mean value. The proposed saliency maps are obtained as follows:

$$D^n = ((|I^n * L|) * g)^{\gamma_1} \tag{5}$$

where D^n is detail saliency maps, γ_1 is gamma weighting for detail saliency.

$$C^n = \left(\sqrt{\frac{(R^n - \mu^2) + (G^n - \mu^2) + (B^n - \mu^2)}{3}} * g \right)^{\gamma_2} \tag{6}$$

where C^n is color saliency maps, R^n, G^n, B^n is red, green, blue channel of multi-exposure image, respectively, μ is mean value of colors, γ_2 is gamma weighting for color saliency.

$$S^n = D^n \times C^n \tag{7}$$

where S^n is final saliency maps. Final saliency maps are obtained by product of Eq. (5) and Eq. (6). In Eq. (5) or Eq. (6), The role of gamma weighting means that if saliency is high, it is to be higher relative, if saliency is low, it is to be lower relative. In this way, we can certainly distinguish between high saliency and low saliency. In Eq. (7), each of saliency maps must be normalized

5. Experiment

A. *Image Quality Assessment*

To evaluate the performance of our algorithm, we adopt Color Image Quality Index(CIQI) [7]. CIQI is no reference color image quality measure. More specifically, it is a measure of how well color information is expressed. If CIQI value is higher, corresponding image has good quality. CIQI is calculated as follows.

$$I_{rg} = R - G \tag{8}$$
$$I_{yb} = (R+G)/2 - B \tag{9}$$
$$\sigma_{rgyb} = \sqrt{\sigma_{rg}^2 + \sigma_{yb}^2} \tag{10}$$
$$\mu_{rgyb} = \sqrt{\mu_{rg}^2 + \mu_{yb}^2} \tag{11}$$
$$Q_{CIQI} = \sigma_{rgyb} + 0.3 \cdot \mu_{rgyb} \tag{12}$$

where R, G, B is red, green, blue channel of image, respectively, σ is standard deviation, μ is mean value.

B. Experimental result

Our algorithm was implemented in MATLAB and were executed on the same computer with Windows 10, Intel i-5 CPU 3.30GHz, 8-GB RAM. Multi-exposure image dataset listed in Table 1. This image dataset is frequently used to other studies [1~5].

Table 2. shown a performance comparison of the proposed method with a previous MEF method using CIQI quality assessment. The proposed method has higher quality value than previous method.

Table. 1
Input images for the experiment

No.	Name	Size	Number	Image courtesy
1	Arno	870 x 577	3	Bartlomiei Okonek
2	Balloons	512 x 399	9	Erik Reinhard
3	Belguim	1025 x 769	9	Dani Lischinski
4	Ostrow	870 x 580	3	Bartlomiei Okonek
5	Garden	870 x 578	3	Bartlomiei Okonek
6	Garage	348 x 222	6	RASCAL
7	Grandcanal	1200 x 800	3	HDRsoft
8	Iglue	260 x 415	6	RASCAL
9	Laurenziana	800 x 1148	3	Bartlomiei Okonek
10	Hasselt	752 x 500	4	Tom Mertens
11	Chairs	343 x 231	5	RASCAL
12	Mask	1200 x 800	3	HDRsoft
13	Eiffel	530 x 795	3	Jacques Joffre
14	Memorial	512 x 768	16	Paul Debevec
15	Cave	870 x 653	4	M. E. Erb
16	Kluki	870 x 580	3	Bartlomiei Okonek

Table. 2
Performance comparison of the proposed method with previous MEF methods using the CIQI quality assessment

No.	GBF	LPF	GRWF	RFF	GFF	Proposed
1	0.107	0.151	0.138	0.132	0.144	**0.153**
2	0.222	0.225	0.201	0.199	0.240	**0.243**
3	0.085	**0.098**	0.075	0.080	0.092	0.096
4	0.113	**0.143**	0.126	0.127	0.138	**0.143**
5	0.135	0.133	0.107	0.122	0.139	**0.140**
6	0.070	**0.083**	0.060	0.058	0.073	0.079
7	0.074	0.081	0.066	0.074	0.083	**0.086**
8	0.080	0.111	0.096	0.082	0.105	0.111
9	0.120	0.135	0.105	0.125	0.125	**0.138**
10	0.126	0.142	0.112	0.126	0.143	**0.143**
11	0.264	**0.342**	0.305	0.286	0.324	0.323
12	0.117	0.118	0.085	0.107	0.116	**0.121**
13	**0.130**	0.125	0.090	0.123	0.130	**0.130**
14	**0.256**	0.235	0.221	0.216	0.252	0.247
15	0.056	0.065	0.059	0.058	0.061	**0.062**
16	0.140	0.156	0.138	0.147	0.153	**0.158**
Avg.	0.131	0.146	0.124	0.129	0.145	**0.148**

The comparison result between GFF method and the proposed method on the "Laurenziana" image in Fig. 2. Sky and land color is not persevered in the result of the GFF method image. GFF method used only detail measure. But our method is considered color information, so the sky and land is more vivid appearance. But our result still has hallo artifact.

The comparison result between GFF method and the proposed method on the "Belguim" image in Fig. 3. Wall color is not persevered in the result of the GFF method image. But our algorithm result is the more vivid appearance.

5. Conclusion

In GFF method, the saliency is calculated by only Laplacian. And this caused the problem of missing color information. To solve this problem, we considered not only detail saliency but also color saliency. So, we can be achieved colorful fused image. Also, we proved that our algorithm is a good performance by measuring image quality index. However, our result still has halo artifact. In future work, we will explore to reduce the effects of the halo effect.

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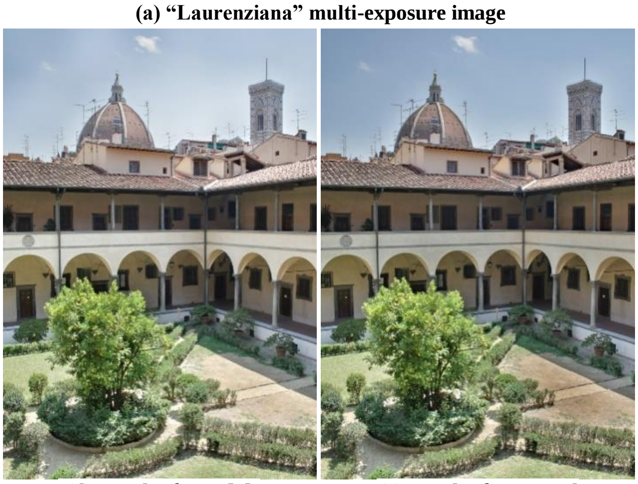
(a) "Laurenziana" multi-exposure image



(d) Result of GFF[4] **(e) Result of proposed**

Fig. 2. Comparison of the proposed method with GFF[4] method using the "Laurenziana" multi-exposure image

(a) "Belguim" multi-exposure image

(b) Result of GFF[5]

(c) Result of proposed method

Fig. 3. Comparison of the proposed method with GFF[5] method using the "Belguim" multi-exposure image

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Biographies

Changho Song received his B.S. degree in Electronic Engineering from Korea National University of Transportation, Chungju, Korea in 2015, and his M.S. degree in image engineering from Chung-Ang University, Seoul, Korea, in 2015. His research interests include multi-exposure image fusion, and low-light enhancement.

Soowoong Jeong received his B.S. degree in multimedia from Namseoul University, Cheonan, Korea in 2010, and his M.S. degree in image engineering from Chung-Ang University, Seoul, Korea, in 2012. He is currently pursuing a Ph.D. at Chung-Ang University. His research interests include image enhancement, de-hazing, and retinex.

Sangkeun Lee (SM'12) received his B.S. and M.S. degrees in electronic engineering from Chung-Ang University, Seoul, Korea in 1996 and 1999, respectively, and his Ph.D. in electrical and computer engineering from Georgia Institute of Technology, Atlanta, GA in 2003. He is an associate professor of the graduate school of Advanced Imaging Science, multimedia and Film at Chung- Ang University, Seoul, Korea. From 2003 to 2008, he was a staff research engineer with the Digital Media Solution Lab, Samsung Information and Systems America, Irvine, CA, where he was involved in the development of video processing and enhancement algorithms (DNIe) for Samsung's HDTV. His current research and development interests include digital video/image processing, denoising, compression for HDTV and multimedia applications, and CMOS image sensors.