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RECURSIVE FILTER BASED DETAIL ENHANCED MULTI-EXPOSURE IMAGE FUSION

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Abstract- The Multi-scale exposure fusion technique is an efficient image enhancement for a high dynamic range (HDR) scene. Several fusion algorithms have been introduced in recent years to combine significant data from various input images into a single fused image. In view of the problems of irregular exposure in the image acquisition and the severe loss of particulars in the conventional multi-exposure image fusion algorithms. The basic idea of the exposure fusion is to retain details in both quite dark and relatively bright regions without representation of HDR image and tone mapping step. The proposed algorithm better preserves the details in the most bright and dark regions of the HDR scene. This paper proposes a weighted technique to multi- exposure image fusion to better retain details, considering features like local contrast, exposure brightness and color information. To eliminate the noise and interference, using recursive filter. Moreover, the proposed method is quite fast and it can be used directly for most consumer cameras. Experimental results shows that the proposed method is superior in terms of subjective and objective analysis.

Key words: Image fusion, Multi exposure fusion, HDR image, recursive filter

I.Introduction

In recent years, image fusion has become a key research area in the field of information fusion. Images captured by standard digital cameras usually suffer from a lack of details in areas that are under-exposed and over-exposed if the camera has a low or high exposure settings. This problem solves by taking multiple images at different exposure levels and merging them together in High dynamic range (HDR) imaging. In digital camera and mobile phone devices this technique has been commonly used. The existing approaches to HDR imaging can be partitioned into two classifications: tone mapping based methods and image fusion based methods.

Tone mapping methods are based on two main steps: HDR image construction and tone mapping. Multiple photographs of low dynamic range (LDR) are first captured and combined to generate a HDR image [2]. Then the overall contrast of the HDR image is diminished by using tone mapping methods [3] to make it easier to project HDR images on devices with a lower dynamic range. This two stage work process i.e., HDR image construction and tone mapping, can produce a tone mapped image in which all areas seems to be well exposed. Many efficient tone mapping techniques have been proposed [4]-[6]. For instance, a tone mapping method based on Retinex model proposes in Kim et al [4]. A new image appearance model and use it for tone mapping in Kuang et al [7]. However, these type of techniques usually takes time and is therefore not well suited for standard digital cameras.

Unlike tone mapping methods, image fusion methods, i.e. multi- exposure image fusion, can ignore the HDR image building process and directly produce a tone mapped like fused image. Multi-exposure image fusion is recommended for consumer electronic applications because it does not require the HDR imaging process which increase some computing cost. Several methods for multi- exposure image fusion have been proposed. For example, a multi-scale image fusion framework proposes in Mertens et al [8]. The source images are first disintegrated as Laplacian pyramids and then mixed together at each level to create the merged image. The performance of such methods may be unsatisfactory if the decomposition level is too high or too low. To address this issue, this paper proposes an image fusion technique based on a weighted sum without multi scale analysis. The fundamental assumption of most existing multi- exposure fusion techniques is that the scene is static in various captures.

The concept of detail enhancement for the exposure fusion image was first proposed in [1]. For each input image a gradient vector is generated taking into account the exposure quality of each pixel. The weighted average of all gradient vectors is then obtained by taking all the gradient vectors of all input images into consideration. To obtain a detail layer from the gradient vector an improved optimization problem of the weighted least square optimization is used in [15]. Finally, the details are added to the fused image produced by [8] to obtain an detail enhanced exposure fusion image.

The proposed algorithm for detail enhancement is much faster than that in [1]. Moreover, the visual quality of the enhanced images in the proposed algorithm is better than that of the algorithm in [1]. Lately, an efficient multi-scale exposure fusion algorithm based on edge- preserving pyramid has been proposed in [16]. The algorithm in [16] cannot, preserve details in the saturated regions, particularly the brightest regions, as well as the tone mapping methods [4]-[6].

This paper proposes a simple but efficient multi-exposure image fusion method. A method of refining the weight map based on recursive filter [14] is used to obtain accurate weight maps for weighted image fusion. The proposed image fusion method is quite fast and thus is well suited for consumer cameras. Experiments on images taken at static scenes illustrate the superiority of the proposed method in objective and subjective evaluation. In addition, it is demonstrated that the proposed method can be used in other applications for image fusion.

II. PROPOSED METHOD

In order to better preserve the image details to show the richest image information, a multi-exposure image fusion method with detail preservation using filters proposes in this paper. Firstly, three characteristic image indexes are calculated: local contrast, exposure brightness and color information, the characteristic index results are used to calculate the pixel weights of different source images and then refined by recursive filtering with the corresponding source image as the reference image. The fused image is finally built by a weighted sum of source images. The schematic diagram of proposed weighted sum based image fusion method as shown in Fig. 1.

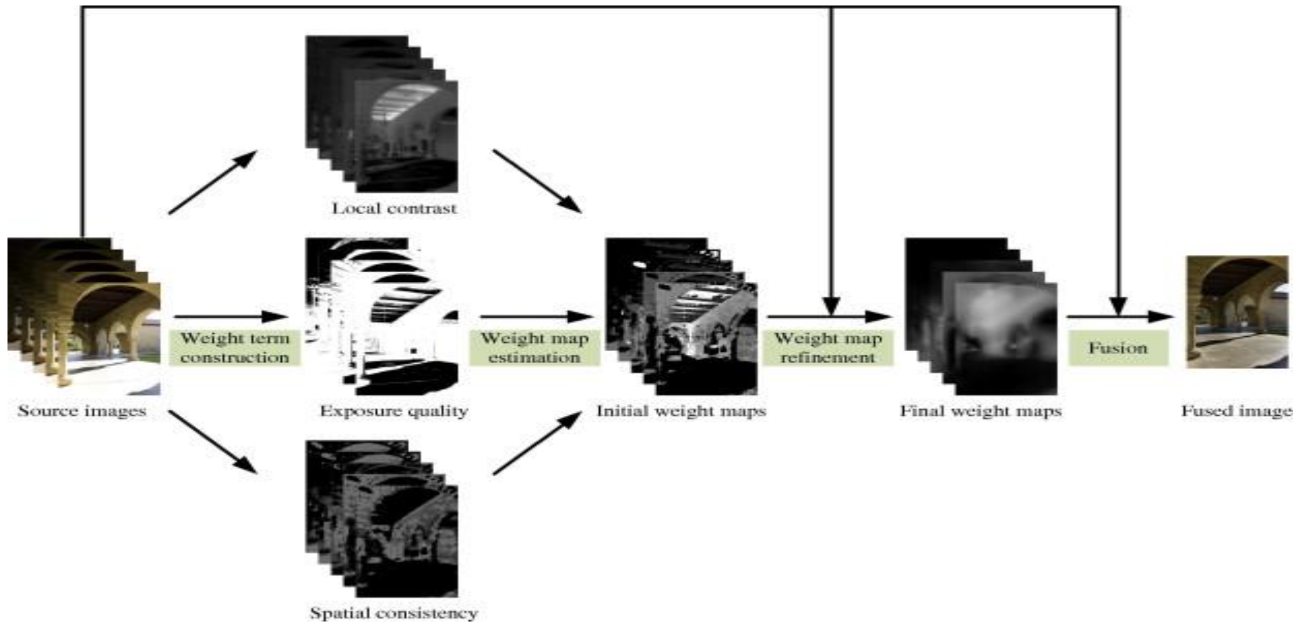


Fig. 1 Schematic diagram of the proposed multi-exposure image fusion method.

A. Local Contrast

Image features, i.e. local contrast and brightness, should be considered for weight estimation when fusing images in static scenes. Each pixel's local contrast is calculated as follows:

$$A_n(x,y) = \widehat{I}_n(x,y) * h(x,y) \tag{1}$$

Where * refers to convolution operation, $\widehat{I}_n$ is a gray image and h is a high-pass filter.

As the local contrast of each pixel is achieved, the resulting local contrast as follows:

$$\hat{A}_n(x,y) = \begin{cases} 1 & if\ A_n(x,y) = \max\{A_n(x,y), n = 1,2,....., N\} \\ 0 & otherwise \end{cases} \tag{2}$$

Where $\hat{A}_n$ is the resulting local contrast feature to preserve image details and N is the number of source images.

B. Brightness

Each pixel's brightness is used to determine whether a pixel is under-exposed or over-exposed. This function ensures that the fused image is not created by pixels from under- exposed, over- exposed areas. Based on the fact that pixels are usually under-exposed or over-exposed with very low or strong brightness, the brightness of each pixel can be observed as follows:

$$B_n(x,y)=\begin{cases}1 & T<\hat{I}_n(x,y)<255-T\\ 0 & otherwise\end{cases} \tag{3}$$

Where T is a threshold value that should be an integral value between 10 to 30.

C. Color Dissimilarity

A novel histogram equalization and median filter based method is proposed by measuring the color dissimilarity between pixels of source images and pixels of the static background of the scene. Histogram equalization is effective method for image enhancement and is used to adjust image intensities to improve contrast. Median filtering is a nonlinear way of remove noise from images. It is widely used because it is very effective in noise removal while maintaining edges. Median filtering is carried out to obtain the median image of the histogram equalized image sequence as follows:

$$I^M(x,y)=median\{I_n^E(x,y)\} \quad n=1,2,....,N \tag{4}$$

Where I^M is the median image i.e., the scene's static background image and I_n^E is the n^{th} histogram equalized image.

Evaluate the color dissimilarity between each histogram equalized image and the static background image of the scene as follows:

$$\tilde{C}_n(x,y)=\exp\left(\frac{(I_n^E(x,y)-I_n^M(x,y))^2}{\delta^2}\right) \tag{5}$$

Where δ equals 0.1 controls the curvature of the Gauss curve.

Finally, $\tilde{C}_n$ is refined by morphological operators (dilation followed by erosion) to eliminate noise estimation:

$$C_n=(\tilde{C}_n\oplus s_1)\Theta s2 \tag{6}$$

Where C_n is the resulting color dissimilarity feature and s_1 and s_2 are disk-like structure elements with radius r_1 and r_2 respectively.

D. Weight Estimation

To preserve image details and to eliminate influences of under- exposed pixels, over- exposed pixels, the three image characteristics, i.e. local contrast, brightness and color dissimilarity, should be combined for weight estimation.

$$D_n=B_n\times C_n \tag{7}$$

Then, D_n is normalized so that they add to one at each pixel (*x*, *y*).

$$\tilde{D}_n(x,y)=\left[\sum_{m=1}^{N}D_m(x,y)\right]^{-1}D_n(x,y) \tag{8}$$

Next, under average score of these pixels i.e., 1/ *N* are defining as zero so that the pixels of different LDR images at the same location will not be all considered as under-exposed, over-exposed.

$$\hat{D}_n(x,y)=\begin{cases}0 & \tilde{D}_n(x,y)<1/N\\ 1 & otherwise\end{cases} \tag{9}$$

Where *N* is the number of source images and $\hat{D}_n(x,y)=0$ means that the n^{th} source image pixel (*x*,*y*) is under-exposed, over-exposed. Finally, $\hat{D}_n$ and the local contrast feature $\hat{A}_n$ are combined to compute the weights:

$$\hat{W}_n=\hat{A}_n\times\hat{D}_n \tag{10}$$

E: Weight Refinement and Weighted Fusion

As shown in Fig.1, the above estimated weights are noisy and hard (mostly weights are either 0 or 1). So the weight maps should be refined for weighted sum based image fusion. This can be achieved by the recently proposed recursive filter [14], which is an edge-preserving smoothing filter in real time. Recursive filtering is carried out on the weight maps $\hat{W}_n$ with the appropriate source image I_n as the reference image.

$$W_n=R(\hat{W}_n,I_n) \tag{11}$$

Where *R* refers to the recursive filtering operation.

After obtaining the resulting weight maps W_n , the resulting fused image I^F can be calculated directly as follows:

$$I^F = \sum_{n=1}^{N} I_n \times W_n \tag{12}$$

III. EXPERIMENTAL RESULTS

In the experiment, we first used the standard images to analyze this proposed algorithm and the weighted guided image filter algorithm (WGIF) has been tested to obtain a preliminary comparison. To objectively evaluate the fusion performance of different methods, two objective fusion quality metrics i.e. entropy and standard deviation are calculated for each fusion algorithm as shown in Table 1&2.

In these experiment shows multi exposure input image sequence of "Tree scenery" in fig.1(a-d), "Garage" in fig.2(a-d) and "Forest" in fig.3(a-c). As per experimental results the proposed technique provides better and gained more details from the fusion results of the input images as shown in fig.1(f),fig.2(f) and fig.3(d), while the other method has darker places, the contrast is extremely low as shown in fig.1(e),fig.2(e) and fig.3(e).

(a) (b) (c) (d)

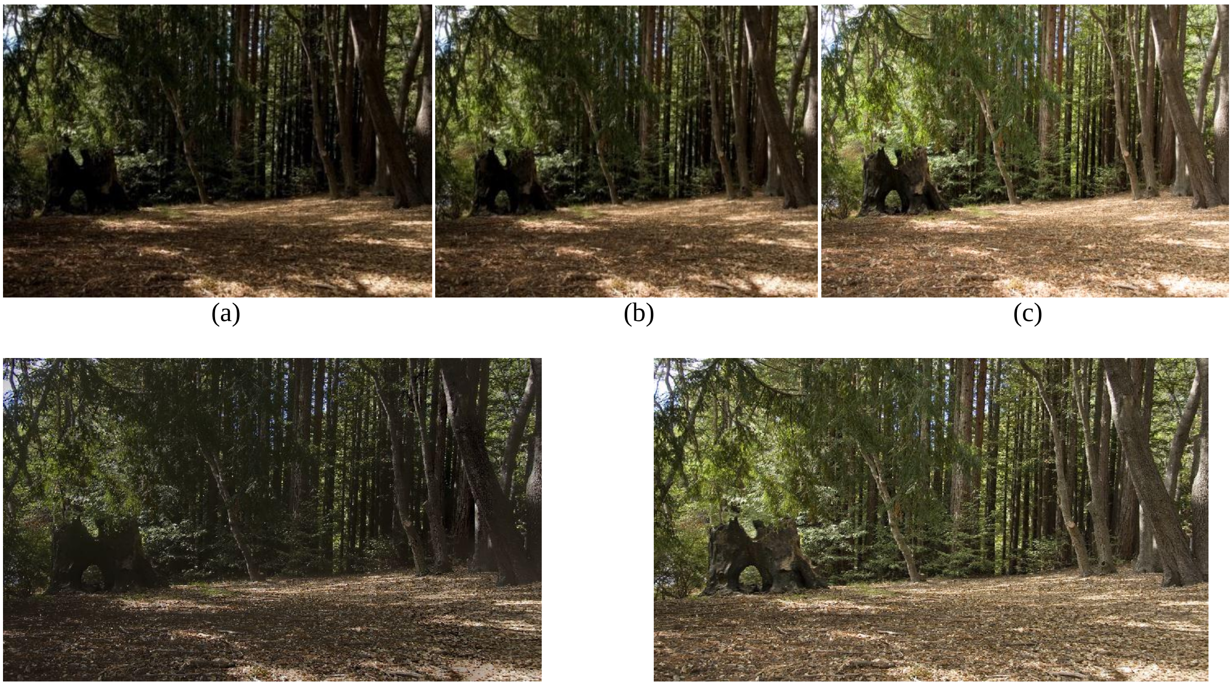
(e) (d)

Fig .2 (a)-(d) input images of Tree scenery ; (e) image fused by WGIF algorithm; (f) image fused by proposed algorithm

(a) (b) (c) (d)

(e) (f)

Fig .3: (a)-(d) input images of Garage; (e) image fused by WGIF algorithm; (f) image fused by proposed algorithm



(a) (b) (c)

(d) (e)

Fig .4: (a)-(c) input images of Forest; (d) image fused by WGIF algorithm; (e) image fused by proposed algorithm

TABLE 1
ENTROPY VALUES FOR MULTI EXPOSURE FUSED IMAGES OF EXISTING AND PROPOSED METHODS

S.NO	Images	Methods	
		WGIF	Proposed
1	Tree Scenery	6.9627	7.6091
2	Garage	6.7475	7.4911
3	Forest	7.1483	7.6318

TABLE 2
STANDARD DEVIATION VALUES FOR MULTI EXPOSURE FUSED IMAGES OF EXISTING AND PROPOSED METHODS

S.NO	Images	Methods	
		WGIF	Proposed
1	Tree Scenery	0.2463	0.2784
2	Garage	0.1485	0.1948
3	Forest	0.2625	0.2840

The larger entropy means that the fused image contains more information and implies better image fusion. The entropy values can be calculated for different multi exposure image fused images obtained by the previous method and proposed method as shown in the Table 1. Standard deviation evaluates the details in the fused image. In image fusion, a larger SD means better image fusion. The standard deviation values can be calculated for different multi exposure image fused images obtained by the previous method and proposed method as shown in the Table 2. The method of this proposed algorithm gives better and gained more details from the fusion results of the input images, while the other method has darker places, the contrast is extremely low. As the data in the table 1&2 shows that the proposed algorithm has a relatively good effect on entropy and standard deviation than the existing method.

IV. CONCLUSION

In this paper, a quick and efficient multi-exposure image fusion approach is proposed. It describes a multi-exposure image fusion algorithm that retains more details. Calculation of the weight map using the selected qualities eliminate the noise and interference by recursive filtering and estimate the weights. Finally, get the fused image with retain details. In addition, the efficiency of the proposed method is illustrated by the use of objective fusion quality metrics. According to the subjective and objective evaluation, especially through the two parameters of information entropy and standard deviation, shows that the proposed algorithm has some advantages and can obtain the high quality of the fused images, retained more details, made a good preparation for the follow-up work.

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