Wavelet Based Exposure Fusion

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Abstract: **A novel method of Multi-exposure image fusion has been proposed in this paper. The images with varying exposures are fused to form a single image that is well exposed and contains the complete details of the scene with proper saturation and exposure. The proposed solution is based on the wavelet transform, in which the coefficients are fused on the basis of weight map that defines the contribution of that image in the resultant fused image. The weight map is based on the well exposedness, saturation and contrast metrics. The wavelet transform offers the multi-resolution blending to smooth the brightness variations in the fused image. The experimental results show that the proposed technique outperforms the previous approaches visually or subjectively**

Index Terms: **High Dynamic Range Image, Image Fusion, L*a*b* Color Space, Multi-exposure Imaging, Wavelet Transform, Weight Map.**

I. Introduction

With the advancement in technology and communication, digital photographs are becoming more and more popular. Whenever, the digital photograph is taken, it will give us the result in the form a two dimensional array, which represents the brightness values [1]. The real world scene may have the significant amount of brightness variations in it but the digital camera has only 8 bits per pixel to store the brightness values. Due to this limited range, images of the sunlit scenes and the scenes with rapidly varying exposure caused by flash or artificial lighting sources end up being too dark or under saturated at some points, and possibly too bright or over saturated at another points [2]. Thus, the low dynamic range of the capturing device limits the computer vision potential. To cater for full dynamic range in such scenes, one can take series of photographs with varying exposures. Then the task will be to combine these images with different exposures to form a single image where all the scene areas appear well exposed.

Exposure is the amount of light that falls on the photographic film or image sensor while taking a photograph [3]. Lens aperture and camera shutter speed are used to determine the exposure time. Faster shutter speed produces short exposure and greater lens aperture produces long exposure. Bracketing is a term used for the process of taking several photographs with different exposure times [3] as shown in Fig. 1. Thus, the images with bracketed exposures are then manipulated by different techniques to get a single image with correct exposure.

Many different approaches have been proposed in the past to solve the problem of multi-exposure images. Some of the work in this area is directed towards creating a High Dynamic Range (HDR) image [4] from the bracketed exposure sequence. The problem with HDR image is that it requires special display devices because the normal display devices have low dynamic range which makes them unsuitable for displaying the HDR image. Therefore, in order to display the HDR image on the normal display devices, the process known as tone mapping [5] is applied to HDR image which reduces the dynamic range of the image thus making it suitable for display.

The other approach of solving this problem is to skip the process of computing HDR image and apply the tone mapping operation. This approach works on the principle of image fusion where the multi-exposure images are fused to yield a high quality low dynamic range image which is suitable for display on normal display devices. Recently Tom et al. have suggested such technique to fuse the images with bracketed exposure [6]. Their technique consists of two main parts:

1. Computing Weight Map from metrics like Saturation, Contrast and Well Exposedness
2. Applying the Pyramidal Image Decomposition for multi-resolution blending and for fusing the images [6].

In the present work, we have extended the Tom et al. approach and have used wavelet decomposition instead of pyramidal decomposition as wavelet offers more efficient and robust representation. The L*a*b* color space is used to extract the true color information of the scene. The perceptual uniformity and a separate luminance component of L*a*b* color space allows it to approximate the human visual perception [7]. The fusion process is independent of each photograph's exposure time and camera parameters. The proposed technique works on the sequence of images of different exposures and it yields a high quality low dynamic range image.

The subsequent sections of this paper are organized as follows. Section II gives the brief overview of the related work. Section III explains the proposed scheme of image fusion. Section IV covers the experimental results and analysis, and is subsequently followed by the conclusion, acknowledgment and references.

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a b c

Figure 1: Example of bracketed exposure a) exposure time 1 sec, b) exposure time 1/4 sec, c) exposure time 1/15 sec.

II. BACKGROUND

Luminance values in HDR images may have a very long range. HDR images can be obtained from the set of multi-exposure images [1, 8, 9] and they can also be obtained through the multi-exposure sensor [2]. The Computer Graphics tools can also be used for this purpose as well.

Debevec et al. presented a technique to recover the high dynamic range radiance maps from the normal photographs [1]. Their method first identifies the response curve of the imaging device which is used to recover the high dynamic range radiance map. They have used logarithmic mapping to display the high dynamic range radiance map on normal display devices.

The high dynamic range of an HDR image is mapped to the low dynamic range of the display device by using a method known as tone reproduction or tone mapping [5, 9]. Reinhard et al. have used the conceptual framework of the Zone System [5] to manage the choices for the tone reproduction. Instead of computing a single composite image, Pardo et al. have suggested representative set of images which capture complete high dynamic range information of the scene [4].

Apart from tone mapping operators, image fusion has also been applied to this area. Burt et al. have used pyramid transform with simple match and salience measures to perform fusion of multi-exposure images [11]. Pattern selective image fusion has been suggested and used to enhance the dynamic range of the monochromatic and color images [12, 13].

Goshtasby has used the block based approach to fuse multi-exposure images [8]. The blocks containing the most important information have been selected and all such blocks are blended using monotonically decreasing blending functions. The entropy has been used as a measure for optimization when fusing the image [8].

Recently Tom et al. have used quality metrics like saturation, contrast and well-exposedness to guide the fusion process [6]. These metrics will select the good pixels from different images and combine them into the fused image.In this work, we have extended the technique of Tom et al. and employed wavelet transform instead of pyramid transform.

Wavelet is used as a tool for multi-resolution blending in the past as well. Su et al. have used wavelet in creating the mosaic of images [14]. The images are first projected into the wavelet subspaces and then the blending operation is performed. The wavelet is also used as a tool for texture synthesis [15] where, the wavelet transform domain blending approach is used to synthesize the output texture.

In order to perform multi-resolution blending in the case of images with bracketed exposure we have suggested the use of wavelet transform. As wavelet transform is advantageous in terms of the following: it represents the signal in multi-resolution manner, which allows operations to be performed at multiple resolutions and in progressive fashion [16]. The wavelet offers both time and frequency information and its sparse representation results in its faster implementation. The wavelet transform does not operate on color images directly so we have transformed the color image from RGB domain to L*a*b* domain as this will preserve the color information more effectively [7]. After that, the rules are applied separately on each band. The detail discussion of the rules will be covered in the next section.

III. PROPOSED TECHNIQUE

This section describes the proposed fusion scheme. The task is to find an image which contains all the important information of the bracketed exposure sequence. The 'important' here is a vague term, so it can be explained with the help of the quality metrics suggested by Tom et al. [6]. They have suggested three quality metrics namely Contrast, Saturation and Well-Exposedness. These metrics are combined to form a weight map [6], which in turn will be used to guide the fusion process. Multi-resolution blending approach is used in order to get the final fused image and the Wavelet decomposition has been proposed for this purpose.

Pre-registered standard image set is used for analysis and testing purposes. Now, we will first explain the basic quality measures as suggested by Tom et al. [6].

3.1 Quality Measures and Weight Map Construction

Sometimes some areas of a photograph appear too bright thus the details present will not be visible in those areas, same is the case when some areas appear too dark. Thus, in both the cases the information is not available, so we do not want such areas to be present in our final fused image. It can be guaranteed by using such measures which assign less weight to such areas, and on the other hand apply high weights to area which are not under or over exposed. The quality measures are described below:

3.1.1 Contrast

As we want to preserve important details such as texture and edge information so we have used this metric.

As suggested by Tom et al. [6], it is calculated by first applying the Laplacian filter to the grayscale version of each image of the bracketed exposure sequence, and then taking the absolute value of the Laplacian Filter response. Contrast is denoted by symbol *C*. For details refer to [6].

3.1.2 Saturation

As we are dealing with color images so saturation here refers to the intensity of a specific color. In RGB color space, we can compute the saturation by applying the following formula.

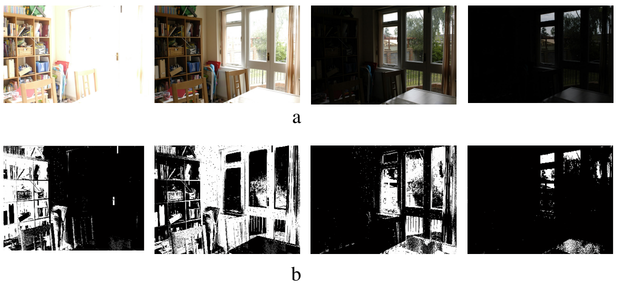

Figure 2: Correspondence between Images and their Weight Maps, a) shows the House Image sequence and b) shows the corresponding Weight Maps of that sequence.

$$\mu = \frac{R+G+B}{3} \tag{1}$$

Here, μ refers to mean of the R(Red), G(Green) and B(Blue) color channel coordinates. The Saturation S can be thought of as a standard deviation as shown below:

$$\sigma = \sqrt{\frac{(R-\mu)^2 + (G-\mu)^2 + (B-\mu)^2}{3}} \tag{2}$$

Here, σ refers to standard deviation.

3.1.3 Well-Exposedness

The idea is based on the value of pixels (intensity) in each channel. The extreme values like 0 and 1 denote the areas where the image is under-exposed or over-exposed respectively. So the basic aim is to avoid these extreme values and select the ones belonging to mid-range i.e. between 0 and 1.

Tom et al. have used following method to weigh the intensities. They have used a Gaussian curve to weigh the intensities based on the condition that how close are they to 0.5 [6]. The idea is to assign high weight to those intensity values that are closer to 0.5. This idea is applied to each color channel and the results of each channel are then multiplied to yield the well-exposedness measure E.

$$RE = \exp\left(-\frac{(R-0.5)^2}{2\sigma^2}\right) \tag{3}$$

$$GE = \exp\left(-\frac{(G-0.5)^2}{2\sigma^2}\right) \tag{4}$$

$$BE = \exp\left(-\frac{(B-0.5)^2}{2\sigma^2}\right) \tag{5}$$

$$E = RE \times GE \times BE \tag{6}$$

Here, in equations (3) to (6), the value of σ is 0.2. [6].

As we have computed three different quality metrics, now the task is to combine these into a single weight matrix or weight map. The product rule is used to combine these measures; the power function is used to control the contribution of each measure in the final weight matrix [6].

$$W = C^{WC} \times S^{WS} \times E^{WE} \tag{7}$$

Here, the power terms WC, WS and WE control the influence of measures: Contrast, Saturation and Well-Exposedness respectively on the weight map. If power term is zero for a certain measure then the result of that measure is not used in computation of the weight map [6]. Fig. 2 shows the images with their corresponding weight maps. Those areas that are not over or under saturated, and the ones that have good contrast and are well exposed are assigned high weights.

*3.2 L*a*b* Color Space Conversion*

Human visual system can discriminate far more colors than luminance [8], so we have transformed the original images from RGB domain to L*a*b* Color space so that we can acquire complete information about image and its color. L*a*b* color space is a color-opponent space [7]. Here, L* stands for Luminance and a* and b* represent the color opponent dimensions. Unlike RGB color space, L*a*b* is perceptually uniform color space and the L* component of L*a*b* matches with the human lightness perception.

The L*, a* and b* channels of the images are then processed separately as per the rules discussed in the next section.

3.3 Wavelet Based Fusion

As we have the image in L*a*b* color space along with its corresponding weight map, now the task is to perform the fusion of these images according to their respective weight maps. Let's consider we have N images, now the main algorithm works as follows:

1. Apply Discrete Wavelet Transform (DWT) to weight map sequence up to M levels. Here W_k represents the weight map of kth image, and k varies from 1 to N.

$$\begin{aligned} &H\{W\}_k^1, V\{W\}_k^1, D\{W\}_k^1, H\{W\}_k^2, V\{W\}_k^2, D\{W\}_k^2 \\ &\cdots H\{W\}_k^M, V\{W\}_k^M, D\{W\}_k^M, A\{W\}_k^M \\ &\quad for \quad 1 \le k \le N \end{aligned} \tag{8}$$

   Here $H\{W\}_k^1, V\{W\}_k^1, D\{W\}_k^1$ represents the Horizontal, Vertical and Diagonal subband of weight map of image k at level 1 respectively. $A\{W\}_k^M$ represents the approximation subband of weight map of image k at highest level of decomposition i.e. at level M.

2. Apply DWT to L* part of the image sequence up to M levels. Here I_k represents the kth image's L* part, and k varies from 1 to N.

$$\begin{aligned} &H\{I\}_k^1, V\{I\}_k^1, D\{I\}_k^1, H\{I\}_k^2, V\{I\}_k^2, D\{I\}_k^2 \\ &\cdots H\{I\}_k^M, V\{I\}_k^M, D\{I\}_k^M, A\{I\}_k^M \\ &\quad for \quad 1 \le k \le N \end{aligned} \tag{9}$$

   Here $H\{I\}_k^1, V\{I\}_k^1, D\{I\}_k^1$ represents the Horizontal, Vertical and Diagonal subband of L* part of image k at level 1 respectively. $A\{I\}_k^M$ represents the approximation subband of L* part of image k at highest level of decomposition i.e. at level M.

3. For fusing the approximation subband perform the following steps:

a. First Pre-process the approximation subband of weight map sequence to make sure that it satisfies the following condition for every point (i,j) in the approximation subband.

$$sum_{ij} = \sum_{k=1}^{N} A\{W\}_{ij,k} \qquad (10)$$
$$sum_{ij} == 1$$

Here sum_{ij} refers to the sum of approximation subband coefficients over the weight map sequence (for k = 1 to N) for point (i, j). The condition is that it should be equal to 1.This is required for consistency purposes.

b. Now, as we have to use the approximation subband at the highest level of decomposition i.e. at level M only, so we will normalize the weight map approximation subband coefficients at level M as follows:

$$A\{Norm\_W\}_{ij,k}^{M} = A\{W\}_{ij,k}^{M} / 2^{M} \qquad (11)$$
$$for\ all\ i, j \quad and \quad 1 \le k \le N$$

Here, $A\{Norm\_W\}_{ij,k}^{M}$ is the normalized approximation coefficient at level M for kth weight map at point (i ,j).

c. Now, as we have the normalized weight maps and now we will perform blending:

$$A\{F\}_{ij}^{M} = \sum_{k=1}^{N} A\{I\}_{ij,k}^{M} . A\{Norm\_W\}_{ij,k}^{M} \qquad (12)$$

Here $A\{F\}_{ij}^{M}$ is the approximation sub band of the fused image at level M.

In this way the approximation sub band at highest level of decomposition of the images with bracketed exposure are fused.

4. For fusing the detail coefficients, at every level of DWT perform these steps:

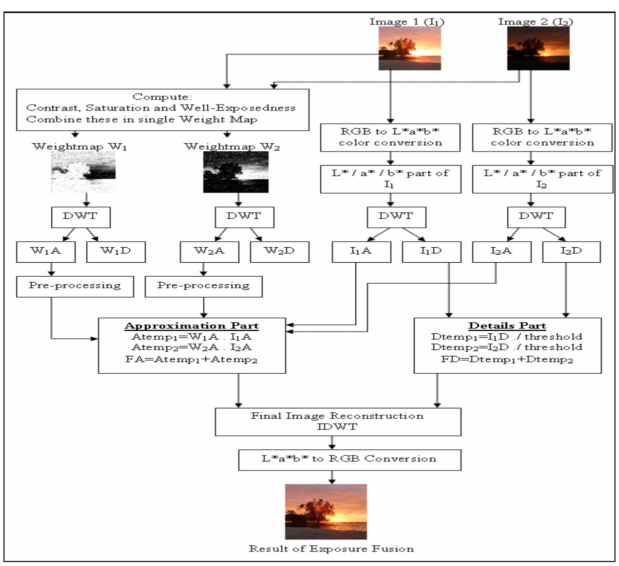

Figure 3: Flow Chart of Main Algorithm for two images.

a. As we have total N images, and we have performed DWT up to M levels so we have the detail subbands as shown below:

$$H\{I\}_{k}^{1}, V\{I\}_{k}^{1}, D\{I\}_{k}^{1}, H\{I\}_{k}^{2}, V\{I\}_{k}^{2}, D\{I\}_{k}^{2}$$
$$\cdots H\{I\}_{k}^{M}, V\{I\}_{k}^{M}, D\{I\}_{k}^{M} \qquad (13)$$
$$for \quad 1 \le k \le N$$

Here $H\{I\}_{k}^{1}, V\{I\}_{k}^{1}, D\{I\}_{k}^{1}$ refers to the horizontal, vertical and diagonal detail subbands at level 1 for kth image's L* part.

b. As those images that are over saturated i.e. too bright and those that are under saturated i.e. too dark contain less edge information so their contribution in the final fused image is less. So those images that have medium saturation contain more edge information so we will get edge or high frequency information from such images.

The idea is to add the detail subbands of all the images and that will give us the detail subbands of the fused image. This idea is explained in terms of the following equations:

$$H\{F\}_{ij,k}^{l} = \sum_{k=1}^{N} \left(H\{I\}_{ij,k}^{l} / threshold \right) \qquad (14)$$

$$V\{F\}_{ij,k}^{l} = \sum_{k=1}^{N} \left(V\{I\}_{ij,k}^{l} / threshold \right) \qquad (15)$$

$$D\{F\}_{ij,k}^{l} = \sum_{k=1}^{N} \left(D\{I\}_{ij,k}^{l} / threshold \right) \qquad (16)$$

Here, the rule is applied for all levels. The threshold is defined to control the edge intensity. In order to avoid too dark edges we have used the threshold. Each detail subband of every image is divided by a threshold to limit the edge intensity.

In this way, we will calculate the detail subbands of the fused image's L* part.

5. Now apply the Inverse DWT (IDWT) to get the fused L* part of the image.
6. Now, repeat step 2 to 5 for a* and b* part of images respectively.
7. As we have fused L* part, fused a* and fused b* part of the image, so now apply the Lab to RGB conversion and recover the fused image in RGB color domain.

This main algorithm is explained in terms of the flowchart shown in figure 3.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

For the evaluation of our algorithm we have tested the technique on a number of bracketed exposure image sets. We have used the pre-registered standard images. The algorithm is independent of the response function of the capturing device and the exposure time of these images. In our experiments we have performed the DWT operation using Symlets wavelet i.e. sym3. Symlets are compactly supported wavelets and their analysis is orthogonal. As we have used the power function to control the contribution of each measure (contrast, saturation and well-exposedness) in the final weight map. So, we have set the value of *WC*, *WS* and *WE* in (7) as 1. In this way all the three measures contribute equally towards the weight map.

In our experiments, the number of levels of decomposition varies with the number of images available. In case we have more than four images of different exposures, then we will use nine levels of decomposition, otherwise we will have eight levels of decomposition. The fusion of approximation subband is straight forward, and has been explained earlier. In case of detail subband fusion, we have to choose an appropriate threshold. The threshold determines that whether the final fused image will be overloaded with details or it will contain the details in seamless fashion. Normal values of threshold that we have used are 2 and 3. In case we have images that vary in brightness to a large extent so we will use threshold 3 in that case, otherwise threshold 2 is chosen and it gives the optimal results.

For evaluation and analysis purpose, we have compared our results with the results of three other well known techniques, namely Radiance Mapping [1], Fusion Method proposed by Goshtasby [8] and Exposure Fusion [6].

In Fig. 4, we have compared our results with these three methods. Fig. 4(a) shows the input image sequence of gold field with bracketed exposure. Fig. 4(b) shows the result of applying Radiance Mapping approach to the input sequence, as we can see the image looks faded, and the colors are not very sharp. Fig 4(c) shows the result of applying Goshtasby's method. The image offers good color contrast. Fig 4(d) shows the result of Tom et al. method, their results offer good color contrast too but, it appears to be dark near the tree side of the image. Fig. 4(e) shows the result of proposed scheme, as it is evident from the figure the image has good color contrast and it provides complete details as

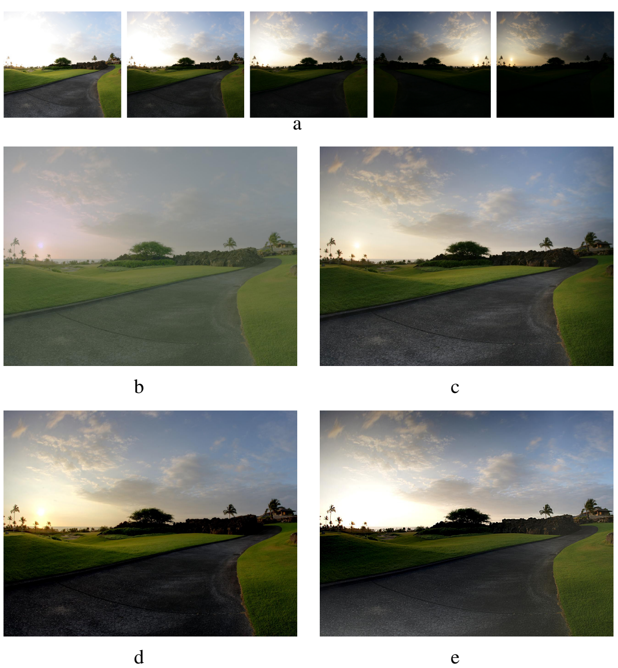

Figure 4: Golf Image Sequence Example

Figure 5: Sunset Image Sequence Example

well. The tree region appears less dark in the image.

In Fig. 5, we have compared the results for the sunset image sequence. Fig. 5(a) shows the image sequence with bracketed exposure. Fig. 5(b) shows the result of Radiance Mapping approach, the image looks faded and the color information is not very prominent in the result. Fig. 5(c) shows the result of Goshtasby's method, the image has good color contrast and it has realistic appearance as well. Fig. 5(d) shows the result of Tom et al. method, the color information is darkened in grass portion of the image, rest of the image offers good color contrast. Fig. 5(e) shows the result of our proposed scheme, the image appears bright and offers complete information about the scene, the color of the grass as well as the sky portion offers good contrast.

As our technique is based on the weight maps that are proposed by Tom et al. in [6], so we will now compare our results with the results of Tom et al. In Fig. 6, we have compared the results for the window image sequence with bracketed exposure. The Fig. 6(a) shows the input image sequence, Fig. 6(b) shows the result of applying the Tom et al. method. The result shows that the image offers good color contrast and provides fine details of the scene. Fig. 6(c) shows the results of our proposed scheme. It is evident from the results that the image has good color contrast and it also provides complete details about the scene. Therefore, the results are almost similar in terms of contrast and preservation of details.

So far, no quantitative measure has been devised to measure the quality of the final image that we get after fusion of images with bracketed exposures. The traditional quality measure like Image Quality Index (IQI) that is normally used to measure the quality of fused image are not applicable here because it measures the quality of the fused image based on the fact that how much details it has acquired from different images. In the case of multi-exposure fusion, some of the images in the sequence do not contribute towards the fusion because they are either too

Figure 6: Window Image Sequence Example

dark or too bright. So some other metric is required that can measure the quality of fused image in the case of multi-exposure image fusion.

So we have compared the results subjectively, and as it is evident by the visual results that proposed scheme outperforms the previous approaches, and in some rare cases it provides the result of equal significance when compared with Tom et al. method.

V. Conclusion

In this paper, exposure fusion scheme based on wavelet transform has been proposed. The fusion process results in a high quality low dynamic range image which is fit to be displayed on a normal monitor. It is a computationally efficient system. The multi-resolution feature of wavelet transform is exploited to blend the image with varying exposures. The brightness variations are smoothed out by proper selection of rules at each level of decomposition and by the proper weighing procedure that is guided by the weight maps. Detail visual or subjective comparison has been made and it proves that the proposed scheme outperforms previous approaches or gives equivalent performance to [6] in some cases. In Future, we would like to devise a metric to measure the quality of the result of multi-exposure fusion and we would like to investigate some other multi-resolution decomposition techniques as well in relevance with the above method.

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