An Illumination And Proficient Photography Image Fusion Based On Gradient Exposure

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***Abstract*— Digital Imaging System have been used in various image processing domains such as satellite and in commercial domain like Voter ID. In the proposed system the series of images are captured by digital camera which has bracketed features (Long Exposure and Short Exposure) and by using a standard dynamic range device (SDR) and synthesizing an image suitable for SDR displays. The SDR device traces scene details like contrasts and gradient direction in a series of SDR images with different coverage levels. The depth of field is first calculated, which helps to find the distance between the nearest and farthest objects in a scene which appears sharp in an images. The scene gradient measure, luminance measure is carried out in order to measure the gradient and increase the contrast of image and last step is integrating the results to get the fusion result. The fusion algorithm techniques are used for fusion of images based on contrast and gradient level. This is done in a multi-resolution of brightness variation in the sequence. Experimental results prove that the proposed scheme does not require any human interaction or parameter tuning for different scenes.**

***Keywords*— Fusion, Gradient, Multi-resolution brightness**

I. INTRODUCTION

Exposure bracketing is one of the important feature in many digital cameras in which a series of pictures are taken in rapid succession with varying shutter speeds. The user picks up one of the best image in the set of images between color information and sharp details. Longer exposure gives good intensity and color information, the result is blurred images; shorter exposure gives sharp details, but these images are usually dark and noisy. Increasing the brightness of the short exposure image (e.g. by global histogram matching with the long exposure image) does not solve the problem. De-noising techniques can avoid problems with the noise, but are not equipped to rectify the color issues.

Two of the most important choices while capturing an image are the photo's exposure level and its depth of field. Ideally, these choices results in noise-free or pixel saturation [1], [2], and appears to be in focus. In order to take a photo there are certain time constraints that has both specific exposure level and a specific depth of field, the camera's sensor should be exposed for a length of time that is dictated by the lens optics.It makes impossible to efficiently take sharp and well-exposed photos of an poorly-illuminated theme that spans a wide range of distances from the camera. To obtain a good exposure level, it must compromise something—either to use a narrow depth of field (and incur defocus blur [3], [4], [5], [6]) nor take a long exposure (and incur motion blur).

II. RELATED WORK

There are a number of related works on fusing sets of photographs. The literature is quite extensive and cannot be covered in its entirety here, but this research work tries to highlight some of the work most closely related to the proposed model. Fattal et al. [7] and Yuan et al. [8], [9] propose algorithms for de-blurring a long-exposure image with a blurry and non-blurry image pair. The blur only comes from camera motion and the scene is static. This prevents these methods from being applied to most pictures with human subjects since some amount of local motion is usually unavoidable.

De-noising and de-blurring image bursts have also been studied. Multichannel blind de-convolution was addressed by Sroubek and Flusser [10], [11] for grayscale images. Telleen et al. [12] and Buades et al. [13] propose techniques that combine a stack of short-exposure images of the same scene to create a noise-free image. The de-blurring work in [10], [11] assumes good image alignment and that the majority of the image scene is static, and the work in [12], [13] assumes each image in the burst is noisy but sharp, so blurring is not an issue. Thus these techniques are not readily applicable to the exposure bracketing problem.

Cross-bilateral filters method combines the color and detail information from the flash image and large scale tonal information from the non-flash image. Local image alignment is required to obtain good fusion result. Variational approach method solves the cross-bilateral method problem using color transfer technique. But still luminance and saturation level is not solved in these methods. This research work concentrates on the image luminance and contrast of the image is increased to obtain the good fusion result which is based on gradient exposure.

III. RESEARCH CONTRIBUTION

A. Image Synthesis

The exposure level of a photo is the total radiant energy integrated by the camera's entire sensor while the shutter is open. The exposure level can be influenced significantly on the quality of a captured photo because when there is no saturation or thermal noise, a pixel's signal-to-noise ratio (SNR) always increases with higher exposure levels. For this reason, most modern cameras can automate the task of choosing an exposure level that provides high SNR for most pixels and causes little or no saturation.

Noise properties and saturation does not affect the exposure level for sensor gain . Lens-based camera systems provide only two ways to control exposure level—the diameter of their aperture and the exposure time. Cosidering all light passing through the aperture will reach the sensor plane, and the average irradiance calculated above the aperture is free of the aperture's diameter. In this case, the exposure level L satisfies,

$$\mathbf{L \; \alpha \; \tau D^2} \qquad \textbf{(1)}$$

Where τ is the exposure time and D is the aperture diameter.

B. Scene Gradient Extraction

A good solution to suppress halos is to apply the scene gradients to adjust the gradient of the synthesized SDR image. The scene gradient information is adaptively captured by setting different exposure levels, i.e., the scene gradients are captured through the local adaptation to the scene luminance for an window $M \times M$ centered at (x, y). Technically, the scene gradient of a point is reflected by the gradient that is perceivable by human eyes, called visible gradient, and that can be measured by counting the number of visible differences of luminance's between neighbouring pixels in the window.

To compute the quantity of the visible gradient $\psi(x, y)$ by,

$$\psi(x,y) = \sum_{i=x-\frac{M}{2}}^{x+\frac{M}{2}} \sum_{j=y-\frac{M}{2}}^{y+\frac{M}{2}} \frac{T(|c(I_H(x,y).}{VMAX(\nabla I_H(x,y))|)} \qquad \textbf{(2)}$$

These stepped exposure levels lead to different gradient magnitudes because the gradient magnitude depends on the image luminances and the image luminance depends on the exposure level. The scene gradient extraction as a process to find gradient $G(x, y)$ that maximizes the quantity of the visible gradient,

$$\mathbf{G(x,y) = arg\; max}_{\nabla I_H(x,y)}\, \boldsymbol{\psi}(\mathbf{x,y}) \qquad \textbf{(3)}$$

Thus Gradient value is measured by using the above formula

C. Luminance Extraction

The image dimensions (width, height and number of channels) are considered to calculate the image luminance (color variance) that maximizes the visible contrasts over different captured images. For each point (*x*, *y*), the image luminance is calculated that maximizes the visible contrasts over different captured SDR images. For point (*x*, *y*) and its surrounding points, which form an $M \times M$ local window in a scene. The visible contrast of the window between the point and its surrounding points is observed. The visible contrast $v(x, y)$ is calculated using,

$$\mathbf{v(x,y) = T(\Delta I_H(x,y))\Delta I_H(x,y)} \quad (4)$$

Where $T(\gamma) = 1$ which is larger than or equal to a predefined threshold.

The different exposure levels lead to different visible contrasts. The visible contrast is weakened at a low luminance level because of the insufficient exposure and is enhanced with the growing of the luminance. However, it is again weakened at a high luminance level because of the overexposure. To observe stronger visible contrast defined by (4) for each point, the exposure level is adjusted to incident-light quantity adaptively, and the visibility of the contrast is consequently enhanced.

D. Fusion

To compute a weighted average along each pixel to fuse the N images, using weights computed from the quality measures. The resulting image R can then be obtained by a weighted blending of the input images:

$$\mathbf{\sum_{k=1}^{N} W_{ij,k} I_{ij,k}} \quad (5)$$

Where I_k is the *k*-th input image in the sequence. 'W' is the weight which varies very quickly, corresponding to the layer that appear.

This occurs due to fusion of images which contains different absolute intensities due to their different exposure different exposure times. The sharp weight map transitions can be avoided by smoothing the weight map with a Gaussian filter, but these results in undesirable halos around edges, and spills the information across object boundaries. An edge-aware smoothing operation using the cross-bilateral filter seems a better alternative. Using the original grey scale image as control image does not work well. Also, it is hard to find good parameters for the cross-bilateral filter (i.e., for controlling the spatial and intensity influence**).**

The input images are decomposed into a Laplacian pyramid, which basically contains band-pass filtered versions at different scales. Blending is then carried out for each level separately. Let the *l*-th level in a Laplacian pyramid decomposition of an image *A* be defined as $\mathrm{Lap}\{A\}^l$, and $\mathrm{Grad}\{B\}^l$ for a Gaussian pyramid of image *B*.

$$\mathbf{Lap(R)_{ij}^{l} = \sum_{k=1}^{N} Grad(W)_{ij,k}^{l}\, Lap(I)_{ij,k}^{l}} \quad \mathbf{(6)}$$

IV. EXPERIMENTAL RESULTS

Home and Land Images are considered with different exposure settings under low light conditions. These images are grouped into single parameter with the help of vectorization concept. The bi-cubic interpolation technique is used to resize the image without lose of pixels in the image.

(A) (B) (C) (D)

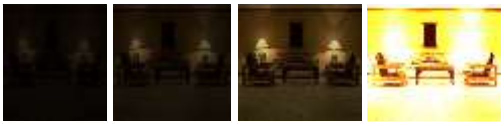
Fig.1. Home Images are taken with different exposure settings under low light conditions.

(A) Short exposure image containing sharp objects but noise, low brightness and poor colors. (B) Long exposure image containing motion blur but no noise and good colors. (C) The brightness of the short exposure image is increased by global histogram matching with the long exposure image. (D) Fusion Based on Gradient Exposure.

(A) (B) (C) (D)

Fig.2. Land Images are taken with different exposure settings under low light conditions.

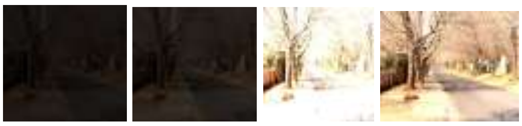
(A) Short exposure image containing sharp objects but noise, low brightness and poor colors. (B) Long exposure image containing motion blur but no noise and good colors. (C) Increasing the brightness of the short exposure image by global histogram matching with the long exposure image. (D) Fusion Based on Gradient Exposure.



(A) (B) (C) (D)

Fig.3. Hall Images are taken with different exposure settings under low light conditions.

(A) Short exposure image containing sharp objects but noise, low brightness and poor colors. (B) Long exposure image containing motion blur but no noise and good colors. (C) Increasing the brightness of the short exposure image by global histogram matching with the long exposure image. (D) Fusion Based on Gradient Exposure.



(A) (B) (C) (D)

Fig 4. Nature Images are taken with different exposure settings under low light conditions.

(A) Short exposure image containing sharp objects but noise, low brightness and poor colors. (B) Long exposure image containing motion blur but no noise and good colors. (C) Increasing the brightness of the short exposure image by global histogram matching with the long exposure image. (D) Fusion Based on Gradient Exposure.

(A) (B) (C) (D)

Fig.5. Window Images are taken with different exposure settings under low light conditions.

(A) Short exposure image containing sharp objects but noise, low brightness and poor colors. (B) Long exposure image containing motion blur but no noise and good colors. (C) Increasing the brightness of the short exposure image by global histogram matching with the long exposure image. (D) Fusion Based on Gradient Exposure.

Home, Land, Hall, Nature and Window images are matched with matched database to identify high frequency regions. Peak Signal Noise Ratio is calculated for these images which gives the quality. PSNR value thus obtained is compared with the two methods of PSNR value. Fusion Based on Gradient Exposure produces the best result when compared with Variational Approach and Cross – Bilateral method. Table 1 and Table 2 shows the calculation of Peak Signal Noise Ratio and Structural Similarity Ratio.

Peak Signal Noise Ratio is calculated by the under mentioned formula. The PSNR and SSIM ratio values are thus calculated and are tabulated. The values are compared by drawing the graph which is shown in Fig 6 and Fig 7 for different methods.

$$PSNR = 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE)$$

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

PSNR is used to measure the quality of image. In the proposed work five datasets are considered in order to obtain the good result with quality and contrast.

TABLE 1: CALCULATION OF PEAK SIGNAL NOISE RATIO FOR DIFFERENT METHODS

Images	Variational Approach (dB)	Cross-Bilateral Filters (dB)	Fusion Based on Gradient Exposure (dB)
Home	+49.56	+48.55	**+51.94**
Land	+46.22	+47.85	**+52.15**
Hall	+46.89	+43.06	**+48.55**
Nature	+49.99	+46.24	**+50.96**
Window	+48.53	+45.76	**+50.17**

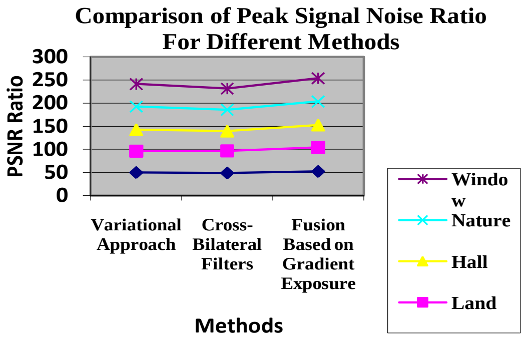


Fig.6. Comparison of Peak Signal Noise Ratio for Different Methods

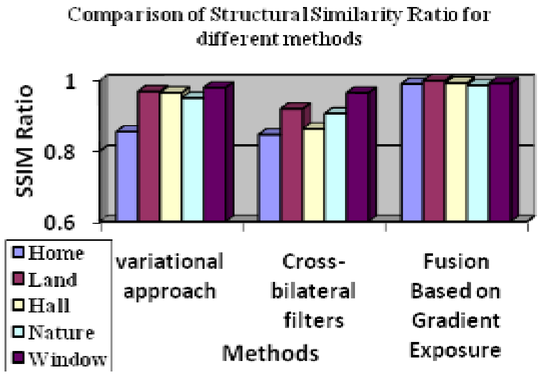


Fig7. Comparison of Structural Similarity for Different Methods

The structural fidelity measure is a full-reference assessment based on the Structural Similarity (SSIM) Index, and the naturalness measure is a non-reference assessment based on statistics of good-quality natural images. SSIM is calculated for five images in this research work and the SSIM values are tabulated.

Table 2: Structural Similarity Ratio Comparison for Different Methods

Images	Variational Approach	Cross-Bilateral Filters	Fusion Based on Gradient Exposure
Home	0.8551	0.8466	**0.9905**
Land	0.9692	0.9200	**0.9998**
Hall	0.9655	0.8633	**0.9932**
Nature	0.9509	0.9064	**0.9866**
Window	0.9799	0.9651	**0.9922**

V. CONCLUSION

A new fusion scheme is achieved in this work by considering local variation and gradient reversal suppression. The visible scene contrasts and the scene gradient can be captured adaptively by utilizing the different exposures. A gradient model has been proposed to carry out the scene reproduction by preserving both the visible contrasts and the gradient consistency. The proposed work maintains visible contrasts and the gradient consistency effectively.

Fusion based on Gradient Exposure technique blends images in a multi-exposure sequence, guided by simple quality measures like saturation and contrast. This is completed in a multi resolution way to preserve the brightness variation in order.

VI. FUTURE WORK

The future enhancement of this work is to improve the color consistency of the fused images; Generalization and expansion of image features can be done to improve their versatility and potential for use on ITER. Further plan is to continue the effort in the area of plasma safety by monitoring issues regarding plasma control, plasma shutdown, and plasma disruptions as they affect safety. A special concentration will be carried out in future for examining the safe shutdown concepts, runaway electron generation and deposition, and liquid surface induced disruptions and their severity to support the reactor concept design studies.

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