Image Restoration by Developing an HDR Image for Minimizing the Blur in Image

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ABSTRACT
It is the age of fast and good quality Digital images, those are subject to blurring due to many hardware limitations, such as atmospheric trouble, apparatus noise and poor focus quality. A high quality image restoration is done by making a High dynamic range (HDR). The (HDR) image generation had been studied in past years. Due to the expense and lack of HDR cameras, a lot of works try to generate HDR images using several low dynamic range (LDR) images with different exposure setting. To ensure high-class HDR image generation and details of the scene should be retained in different LDR images and the exposure parameters of LDR image should be chosen carefully. In this paper our proposed work focuses on the tone mapping techniques with a practice to dynamically determine the suitable exposure parameter for LDR images agreeing to the property of each scene to be seized. The proposed method provides approximately 10% improvement in UIQI in comparison to C.S.Vijay method. Simulation results reveal that better HDR images are always generated with the LDR images held by the determined exposure, compared to those produced by the method with fixed exposures.

Keywords
HDR Imaging, Image Restoration, Exposure Determination

1. INTRODUCTION
Quality of the image can be improved with the concept of lots of images of same object at the same position can be taken as the raw images. And then further proceed the HIGH dynamic range (HDR) imaging is concerned with extraction of latent scene irradiance. The variation in the magnitude of the irradiance can be as wide as 14 orders in the log unit scale. HDR cameras commercially exist but these are very costly. Over the years, some algorithmic methods for estimation of scene irradiance [2], [4], [5] have been suggested. The basic idea is to capture multiple images of a scene with altered exposure settings and algorithmically extract HDR figures from these interpretations. In the scenario of HDR imaging, the requirement for longer exposure times increases the chance of deprivation due to motion blur [3]. Furthermore, in places like, heritage sites or museums, there are restrictions on carrying tripods [1]. Hence, in HDR imaging, developing algorithms to remove motion blur becomes all the more important. The problem of scene irradiance rebuilding in the presence of blurred observations was first discussed by Lu et al. [3]. They consider a set of differently exposed but uniformly blurred images. The rest of the paper is as follows in section 2 we discuss some basics for LDR to HDR construction. The proposed work is discussed in section 3. In section 4, we discuss simulation results and then finally we conclude with section 5.

2. BASICS FOR LDR TO HDR CONSTRUCTION
Due to the expense and lack of HDR cameras, a number of works try to select the most appropriate LDR images to generate the HDR image where many LDR images with various exposures are already captured and stored; it implies that larger storage, as well as higher energy use is essential for such scenarios. It is not guaranteed whether the proper LDR images are already captured. A simple method for HDR imaging is to use the number of LDR images with different exposure value (EV). Although it is reasonable to obtain the HDR image using these exposure settings, the HDR image quality is likely to be not promising due to the characteristics of each scene to be captured as well as varying luminance condition. To overcome this problem, we propose in this paper a technique to smartly determining the exposure parameters. In this way, only the needed LDR images are captured and not only an improved HDR image can be expected due to a supply of more suitable LDR images, but also a lesser power consumption and requirement of storage can be achieved. Generally, there will be more details at the dark region for an image taken with a longer exposure time, and there will be more details at the bright region for the image taken with a shorter exposure time. To make HDR image generation possible, we use several LDR images with different exposure settings. Then, HDR image can be produced by combining number of LDR images.

3. PROPOSED WORK
The image deblurring is performed by generating a HDR image by using the following processing step as shown in the following flowchart.

3.1 Image Acquisition
In this step the Images are introduced in MATLAB for further processing. Here we take 16 various intensity images with different exposure time as an image input sequence.

3.2 Edge extraction using canny operator
The image edges are extracted to preserve the image basic structure to maintain the image quality. For this edge detection and preservation canny operator is used.

3.3 Respective Light Intensity Extraction
In this section, we discuss irradiance estimation from a set of N_E differently exposed intensity images $Z_1, Z_2 . . . Z_{NE}$. To each input image Z_i, the associated TSF K_i, $i = 1, 2 . . . NE$ is calculated correspondingly. The irradiance image map Bi corresponding to observation Zi is given by $Bi = f{-}1(Z_i)/\Delta t_i$, where Δt_i is the exposure time of the observation Zi. Simultaneous de-blurring and extraction of latent HDR

irradiance image can be posed as an optimization problem where the solution can be obtained by minimizing the cost.

$$\sum_{i=1}^{N_E} \left\| K_i E - B_i \right\|^2 \quad (1)$$

Here, E denotes latent irradiance image while K_i is the blurring matrix of the ith exposure that represents the space variant blurring operation. The rows of K_i are local blur filters acting on the pixels of E to yield the blurred irradiance image B_i. The pixel intensity value in an image is a monotonic but nonlinear function of the irradiance and exposure period. The light energy accumulated is given by

$$X = \int_{t=0}^{\Delta t} E dt + n \quad (2)$$

Where E is the irradiance, Δt is the exposure time, and n is additive noise. A series of specialized algorithms alter the collected data in real-time to map the irradiance values to the final image intensities.

3.4 Image alignment

This approach is used to align the different LDR exposures prior to merging them into the final HDR image.

3.5 Select Sample Pixel Nodes

We have considered blind estimation techniques [30] (multi-channel) to estimate the PSFs. We estimate N_p different PSFs of a blurred frame corresponding to local irradiance image patches B_{pj}^k where pj refers to the location of the patch (j= 1, 2, . . . N_p), and k is the index of the frame. At a location the PSFs of the two selected frames (n = 1, 2) are derived by minimizing the following energy function

$$\phi\left(E_{pj}, h_{pj}^1, h_{pj}^2\right) = \frac{1}{2}\sum_{n=1}^{2}\left\| h_{pj}^n * E_{pj} - B_{pj}^n \right\|^2 + \lambda_{TV}\int \left\| \nabla E_{pj} \right\| + \frac{1}{2}.\lambda_k \left\| h_{pj}^2 * B_{pj}^1 - h_{pj}^1 * B_{pj}^2 \right\|^2 \quad (3)$$

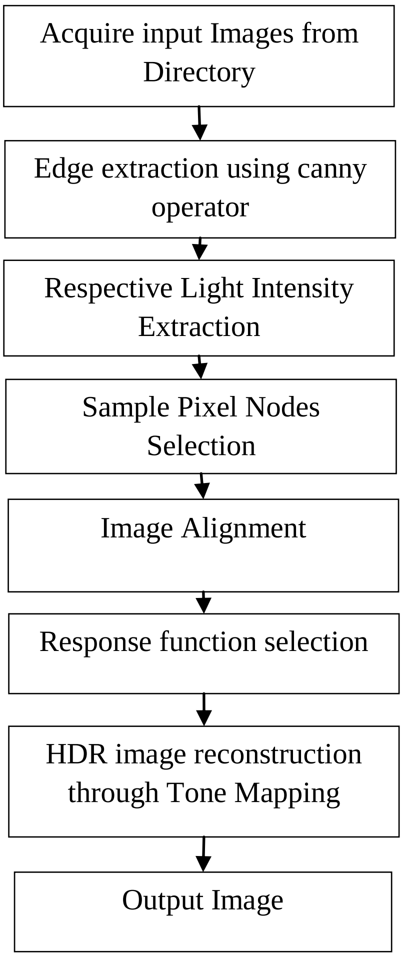


Fig.1 (a): Proposed methodology

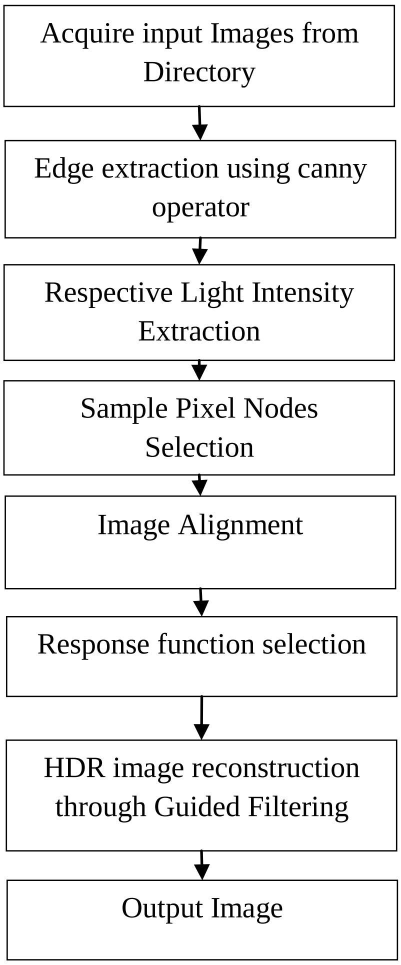


Fig.1 (b): Proposed methodology

Where λ_{TV} and λ_k are regularization parameters, E_{pj} is the estimated latent scene irradiance patch at pj the quantities h_{pj}^1 and h_{pj}^2 are the estimated PSFs at location **p**j corresponding to blurred irradiance patches B_{pj}^1 and B_{pj}^2 in the two selected observations. Following the above procedure, N_p different PSFs are estimated for each of the blurred frames. The PSFs that we estimate using equation (12), though locally accurate, might not be in mutual alignment with respect to the PSFs estimated at other locations. If we attempt to use these PSFs directly in the TSF estimation procedure, then the TSF thus estimated will be erroneous. The true TSFs cannot be estimated without compensating for the shifts among the underlying PSFs. To alleviate this problem, we (randomly) choose one of the PSFs as reference and align other PSFs with respect to it. If $h^2_{p_1}, h^2_{p_2}, h^2_{p_3} .....h^2_{p_{N_p}}$ are the PSFs of the first frame, we choose one of the PSFs (say $h^1_{p_{ref}}$) as reference. The TSF h^1_T is estimated by searching over all possible shifts of the PSFs $h^1_{p_1}$ to $h^1_{p_{N_p}}$. That h^1_T which minimizes the error $\sum_{l=1}^{N_p} \left\| h^1_{p_l} - M_l h^1_T \right\|^2$ is chosen to be the correct one. Note that as a shifted PSF can have correspondingly shifted latent image, many possible solutions for the TSF with correspondingly warped latent images can exist. Hence, the solution (TSF) obtained by our procedure will correspond to one of the warped instances.

3.6 Response Function Selection

the quality of deblurred image mainly determined by the knowledge of point spread function The total quantity of light accumulated on the image sensor during integration time Δt– which is controlled by the shutter – produce sensor exposure

$$I \equiv E\Delta t \tag{4}$$

After exposure, the accumulated charge is converted to integer values using analog -digital converters connected to each photosensitive element on the image sensor. The process of digitization brings quantization noise to recorded data. The individual sources of nonlinearity in the imaging process are not important and the whole process can be represented by one nonlinear function – a camera response function *f*. We see that measured pixel values *M* are proportional to the sensor exposure *I* scaled by the response function

$$M = f(I) \tag{5}$$

3.7 HDR Image Reconstruction

To reconstruct an HDR image H that is aligned to one of them (the reference calledL_{ref}) but contains HDR information from all N exposures from Given set of N LDR sources taken with different exposures and at different times ($t_1, \ldots, t_N$). we include information from all other exposures in places to pose the problem as an energy minimization where L_{ref} is poorly uncovered, the HDR image H in these parts should be "similar" to any input source $L_k$mapped through the response curve of the k^{th}exposure:l_k(H). However l_k(H) need not match L_k exactly, Since the scene and camera are moving because H might not be aligned to both L_{ref} and L_k simultaneously. Minimizing BDS Results that for every patch of pixels in l_k(H) there should be a comparable patch in L_k and for every patch in L_k there is a comparable patch in l_k(H) (called "completeness"), across multiple scales. Combining these two properties together results in an energy equation with two basic terms:

$$E(H) = \sum_{p \in \text{pixel}} \left[\begin{array}{c} \beta_{ref\,(p)} \cdot \left(h((L_{ref})_{(p)} - H_{(p)}\right)^2 \\ + \left(1 - \beta_{ref\,(p)}\right) \sum_{k=1}^{N} \text{MBDS}(H|t_1, \ldots, t_N) \end{array} \right]$$

In this, the initial expression for pixels that are well-exposed ensures that H is alike to $h(L_{ref})$ in a L_2 sense. Using a modified form of BDS (EMBDS) the second term constrains the remaining poorly exposed pixels to match the other exposures. In our input stack, MBDS is applied to all N source images by defining an energy function that tries to keep each exposure n of the HDR image Has alike as possible to all input sources adjusted to that exposure:

$$E_{MBDS}\,(H, |\, t_1, \ldots, , t_N) = \sum_{k=1}^{N} \text{MBDS}\left(l^k(H) \middle| g^k(t_1), \ldots, g^k(t_N)\right) \tag{7}$$

Where $g^k t_q$ is a function that maps the q^{th} LDR source to the k^{th}LDR exposure. To produce the final HDR image this function ensures that every exposure of the HDR image $l^k(H)$ is "similar" to the exposure adjusted versions of all N input images in the regions that their pixels are properly exposed, which will help to bring information from these other exposures. Eq.4 is called the HDR image synthesis equation. In the regions where its pixels are properly exposed, the first term ensures that the algorithm uses information from L_{ref} only. The resulting HDR image H should be a close match to the reference input in these regions. The second term adds information from the other exposures through a bidirectional similarity energy term in the parts of the image where it is over/under-exposed. In one of the LDR inputs after adjusting for exposure (coherence), which makes the final result H look like a consistent image resembling the inputs in these poorly-exposed regions, every patch in the final HDR image H at a given exposure should have a similar patch. So that valid information from the inputs is preserved every valid exposure-adjusted patch in all input images should be contained in H at this exposure.

3.8 Guided Filter

Here we propose a new type of explicit image filter, called guided filter to recover an HDR image. The filtering output is locally a linear transform of the guidance image. Guided filter has the property of edge-preserving smoothing. That's why this filter is used instead of Gaussian filter. The whole process of recovering an HDR image using Guided filter is shown in fig.1 (b)

3.9 Tone Mapping

The high dynamic range image needs to be tone mapped first. a TRC based tone mapping algorithm should assign relatively more display values to lightly occupied luminance intervals and relatively fewer display values to soundly occupied luminance intervals. To fully utilize all existing display levels a TRC based tone mapping algorithm should also maintain the relative visual dissimilarity impressions of the original scene. Therefore, $d_1, d_2, ...d_{255}$, must plunge in between linear scaling and histogram equalization. A tone mapping algorithm should assign relatively more display values to strictly populated luminance intervals and relatively fewer display values to lightly populated luminance intervals.

We can define the following objective function, to formalize this mapping principle,

$$E = \sum_{i=1}^{255}\left(d_i - \frac{i}{256}\right)^2 + \lambda\sum_{i=1}^{255}\left(\int_0^{d_i} h(x)dx - \frac{i}{256}\right)^2 \qquad (8)$$

Optimizing E becomes histogram equalization mapping, and λ = 0 optimizing E becomes linear scaling mapping where λ is the Lagrange multiplier. To suit individual images by choosing an appropriate l, we can strike a balance between the two extreme forms of mapping.

4. SIMULATION RESULTS

On the basis of some performance parameters, the simulation results are analysed. The mean, noise variance σ^2, SNR and universal Image Quality Index (UIQI) are the parameters associated with our algorithms. We need to calculate these parameters.

MEAN: It can be calculated to find that on how average intensity we are working with and how result affects with change in average intensity.

VARIANCE: Because we assume that the noise in the fusion model is a Gaussian noise, To calculate approximately the noise variance by this equation

$$\sigma^2 = \frac{1}{MN}\sum_i (Y_i - H_i X)^T (Y_i - H_i X) \qquad (9)$$

The pdf of H is known to be a difficult problem [9] ,the direct ML estimation of the parameters associated with.

SNR: The SNR in decibels, as shown in (19), is a direct index to compare the fused image to the reference one [12]. For multiband images, it can be calculated band-by-band and also globally averaged SNR

$$\mathrm{SNR}\,(Z, \hat{Z}) = 10\log_{10}\frac{\sum Z^2}{\sum(Z-\hat{Z})^2} \qquad (10)$$

Universal Image Quality Index (UIQI): A UIQI [8] has been widely used for image similarity evaluation and was also applied to validate fusion techniques [7]. UIQI of two images (A and B) is defined as

$$Q = \frac{4\sigma_{AB}\,\mu_A\mu_{\boldsymbol{B}}}{(\sigma_A^2+\sigma_B^2)(\mu_A^2+\mu_B^2)} = \frac{\sigma_{AB}}{\sigma_A\sigma_B}\cdot\frac{2\mu_A\mu_{\boldsymbol{B}}}{\mu_A^2+\mu_B^2}\cdot\frac{2\sigma_A\sigma_B}{\sigma_A^2+\sigma_B^2} \qquad (11)$$

This class index models any distortion as a combination of three different factors: correlation loss, luminance bend, and contrast twist. The dynamic range of Q is [−1, 1], and the best value 1 is obtained if A = B. This index is applied band-by-band and averaged over all bands and several scenes are captured to evaluate the performance of the proposed algorithm and two of them are presented here. For each scene the aperture is the same for each captured image and only the exposure time is changed during LDR image capturing. Numerous scenes are captured to evaluate the performance of the proposed algorithm and two of them are presented here. The LDR images of different light intensities are shown in figure 2.

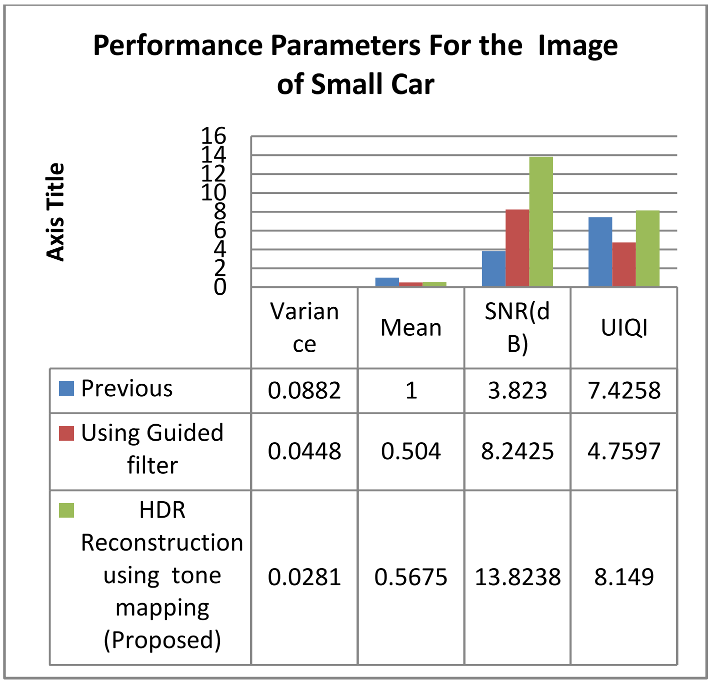
Fig.2: LDR images of small car of different intensity

Fig 3.(a): Result of C.S. Vijay method

Image after using Guided Filter

Fig3. (b): Image after using guided Filter

Fig 3. (c): HDR reconstruction using Tone mapping



	Variance	Mean	SNR(dB)	UIQI
Previous	0.0882	1	3.823	7.4258
Using Guided filter	0.0448	0.504	8.2425	4.7597
HDR Reconstruction using tone mapping (Proposed)	0.0281	0.5675	13.8238	8.149

Fig4. Comparison chart (Proposed method)

5. CONCLUSION

In this paper An habitual exposure determination technique is proposed. After the well-exposed image is captured automatically, two images, providing details in the under-exposed and overexposed situations can be well captured where the exposure is determined in the scene by metering on the most appropriate region. The experimental results show that the proposed algorithm is able to generate the HDR image with high quality and more contrasts can be preserved in the HDR image, compared to those generated by the method with fixed exposures.

6. FUTURE SCOPE

The emerging techniques that seem to hold promise for further research, improvement of the image at edges will be one area that requires a good deal of research. The most critical fault of most of the algorithms discussed in this project is that they assume knowledge of the PSF of the imaging system. This makes studies into the blur removal problem all the more important to the future of this field. Researchers coming from astronomical and medical imaging fields, certainly have additional and valuable viewpoints on this topic that will also help to guide the direction of research in the field.

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