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RADIANCE DOMAIN COMPOSITING FOR HIGH DYNAMIC RANGE IMAGING

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Abstract
High dynamic range imaging aims at creating an image with a range of intensity variations larger than the range supported by a camera sensor. Most commonly used methods combine multiple exposure low dynamic range (LDR) images, to obtain the high dynamic range (HDR) image. Available methods typically neglect the noise term while finding appropriate weighting functions to estimate the camera response function as well as the radiance map. We look at the HDR imaging problem in a denoising frame work and aim at reconstructing a low noise radiance map from noisy low dynamic range images, which is tone mapped to get the LDR equivalent of the HDR image. We propose a maximum aposteriori probability (MAP) based reconstruction of the HDR image using Gibb's prior to model the radiance map, with total variation (TV) as the prior to avoid unnecessary smoothing of the radiance field. To make the computation with TV prior efficient, we extend the majorize-minimize method of upper bounding the total variation by a quadratic function to our case which has a nonlinear term arising from the camera response function. A theoretical justification for doing radiance domain denoising as opposed to image domain denoising is also provided.

Keywords:
High Dynamic Range Imaging, Denoising, Maximum Aposteriori Probability (MAP), Total Variation (TV), Majorize-Minimize

1. INTRODUCTION

The range of intensity variations that the human eye experiences during a day is usually very large, for example the light of the sun at noon is around 100 million times more than that of the starlight [15]. The human visual system copes with this large range by adapting to the prevailing conditions of illumination, and through this adaptation it can function over a range of 10 orders of magnitude. Within a scene the visual system functions over a range of 5 orders of magnitude. Display devices like CRT, LCD and the cameras are not capable of reproducing such a large luminance range. These devices are not capable of handling a range greater than 2 orders of magnitude, which leads to irretrievable loss of information in the scene. Using high dynamic range imaging techniques, an image with intensity variations commensurate with the original scene can be generated; even when the data is captured using dynamic range limited devices.

Many of these high dynamic range (HDR) imaging techniques use low dynamic range (LDR) images which are captured at different exposure settings for creating the HDR image [1, 9, 18, 23, 25, 26, 28, 31]. These methods estimate the non-linear relationship between exposure and image intensity and hence the radiance map. This non-linear relation is named the camera response function (CRF). Given the CRF, the radiance map of the scene being imaged is calculated as a weighted average of the radiance map corresponding to each of the LDR images.

A large class of the proposed methods differs only in the way the weighting function is selected [9, 18, 23, 25, 31] and they cannot appreciably handle noisy data. However noise in the data is inevitable, more so when the exposure time is small. Other methods [1, 26, 28] apply statistical methods for obtaining the inverse camera response as well as the radiance map. While these methods do address the issue of possible noise in the observations, the noise is handled mainly by selecting appropriate weights, to obtain the camera response function and hence the HDR image and they fail to denoise the HDR image appreciably.

The method of Mann and Picard [23] obtains the camera response function from LDR images and uses the derivative of the camera response function as the weighting function for combining the images. Debevec and Malik [9] uses a hat function for weighting the pixels. Weighting functions based on signal to noise ratio and output standard deviation are considered in the work of Mitsunga et al. [25] and Tsin et al. [31]. Miguel et al. [18] propose a weighting function which takes into consideration the spatial and temporal noise.

Among the statistical methods, Robertson et al. [28] use maximum likelihood approach to estimate the high dynamic range image; their formulation deals with the cases of known and unknown camera response functions. Pal et al. [26] propose a Bayesian network based probabilistic model for high dynamic range imaging. An alternate method for noise reduction is proposed by Aky et al. [1] in which a weighted averaging in radiance domain over a fixed number of frames is done to reduce the noise. Other methods used in literature include bilateral filtering [14]; wavelet based denoising of the LDR images before combining them to form the HDR image [20] and multi-frame denoising when the camera is in motion [24].

Image denoising is one of the widely explored areas in image processing. There are several methods reported in the literature for denoising. We list a few here indicative of the different approaches. Wiener filter [33], is an optimum linear filter for denoising, but has the problem of over smoothing the image. Wavelet shrinkage based denoising methods depends on the fact that the magnitudes of wavelet coefficients are directly proportional to the irregularity of a given image. Denoising can be achieved by properly suppressing the irregularity of wavelet coefficients due to noise. The theoretical foundations and different approaches to wavelet shrinkage are reported in [6, 10, 12, 13, 22].

Edge preserving denoising methods include Geman and Geman's Bayesian image restoration [17], and total variation based denoising which was first introduced by Rudin and Osher [29, 30], based on which numerous works have been reported [3, 7, 8, 11, 21, 32]. Another approach to denoising is via nonlinear diffusion, reported by Perona and Malik [27] in which diffusion coefficient giving edge selectivity was used. Recent works include unsupervised information theoretic adaptive filtering [4] and the non-local means algorithm [5].

We propose a restoration framework for generating a less noisy HDR image from multiple exposures, noisy LDR images with known exposure times. The radiance map is reconstructed using Bayesian methods. The posterior probability density function for the radiance is obtained given the noisy observations having different but known exposure times. Since the observations are a nonlinear function of the radiance, finding the optimum radiance involves solving a set of nonlinear equations. In the work by Debevec et al. [9] even though a smoothness term is used while solving for the camera response function, it is seen that the generated radiance map is noisy. In our work, we take this noisy radiance map and do the denoising in the radiance domain to obtain a better quality image, leading to compositing as well as denoising.

We first formulate a GMRF prior which is then replaced by a total variation based prior. Our formulation requires the knowledge of camera response function (CRF). Hence we estimate the CRF using the method of Debevec [9]. Work on similar lines where radiance domain formulation is done is reported for a single, low dynamic range image reconstruction in the work of Hunt [19], wherein the nonlinear relation between radiance and intensity is considered. In [19] the MAP estimate directly reconstructs the intensity from a single observation as opposed to our formulation which reconstructs the radiance map from multiple, noisy LDR images.

It is observed that the GMRF prior leads to excessive smoothing, so we propose a TV based prior which would be equivalent to a Laplacian distribution. This yields better results where the edges are well preserved and noise is reduced considerably. We also propose an adaptation of the majorize-minimize method of Figueiredo et al. [16] originally proposed for a linear case, to our nonlinear formulation, through iterative linearization for drastically speeding up the computation for the case of TV based prior. We also show theoretically that looking for a solution in the radiance domain as opposed to image domain is well justified.

2. PROPOSED METHOD

The image formation model used is

$$Y_i = g_i(R)+N_i \quad i = 1\ldots k, \tag{1}$$

where, Y_i are the observed LDR images, each having a different but known exposure time, i denotes the exposure time. The function g_i maps radiance (R) to intensity Y_i corresponding to the i^{th} exposure. This function is obtained from the camera response function which maps intensity to exposure. Exposure is defined as the product of radiance and exposure time. As the camera response function varies with the camera settings, g_i is different for different i. N_i is a sample of additive white Gaussian noise. Without loss of generality it is assumed that the noise variance is same for all exposures.

Due to the presence of noise in the observations, the estimation of CRF and hence that of the radiance map suffers, leading to a tone mapped image which is still noisy. This is observed in Fig.2(a) which shows the high dynamic range image reconstructed using the method of Debevec [9]. Even though they use smoothness regularization, the reconstructed HDR image still shows noise. In our approach, we aim to reduce this noise by finding the radiance value which maximizes the posterior distribution of radiance, given the observations Y_i,

$$f_{R|Y}(R\,|\,Y) = \frac{f_{Y|R}(Y\,|\,R)\,f_R(R)}{f_Y(Y)} \tag{2}$$

where, Y is defined as $Y = [Y_1 \;\ldots..Y_K]$. For a given radiance R and g_i which is already estimated, it is observed from Eq.(1) that Y_i are independent Gaussian random variables with mean $g_i(R)$. This gives,

$$f(Y\,|\,R)\alpha \exp\left(\sum_{i=1}^{k} -\frac{(Y_i - g_i(R))^T (Y_i - g_i(R))}{2\sigma^2}\right) \tag{3}$$

Since the scene satisfies the smoothness properties of an image, it can be modeled as a Gaussian Markov random field. Since the Gibbs random field and Markov random field are equivalent, the probability density of the radiance field is written using the Gibb's equivalent distribution as [2],

$$f(R) = \frac{\exp(-\beta U(R))}{Z}, \tag{4}$$

with β a regularization constant and

$$U(R) = \sum_{l}\sum_{k\in N_l}(r_l - r_k)^2, \tag{5}$$

where, l indexes the pixels in the image and N_l represents the 4-neighborhood of l, r_l is the radiance value at the l^{th} pixel location, and Z is a normalization constant known as the partition function. Let $\hat{R}$ be the radiance that maximizes Eq.(2), i.e.,

$$\hat{R} = \arg\max_R f_{R|Y}(R\,|\,Y). \tag{6}$$

$$\hat{R} = \arg\min_R \lambda \sum_{i=1}^{k}(Y_i - g_i(R))^T (Y_i - g_i(R)) + U(R), \tag{7}$$

where, λ is the regularization factor. Eq.(7) is a variational problem and is solved iteratively as,

$$r_{k,l}^{t+1} = r^{-t} + \frac{\lambda}{4}\sum_{i=1}^{k}\left[y_{k,l} - g_i(r_{k,l}^t)\right]g_i^{'}(r_{k,l}^t), \tag{8}$$

where, $r^{-t} = \frac{\lambda}{4}\left[r_{k,l+1}^t + r_{k,l-1}^t + r_{k+1,l}^t + r_{k-1,l}^t\right]$, r_k^t is the radiance of the point in the scene corresponding to the $(k, l)^{th}$ pixel in the image, t is the iteration number and $g_i^{'}(.)$ is the derivative of $g_i(.)$. This computation requires the knowledge of $g_i(.)$ which is obtained as explained next.

2.1 ESTIMATING THE MAPPING BETWEEN RADIANCE AND INTENSITY

The function $g(R)$ used in Eq.(1) maps the scene radiance to the image intensity. We estimate this function using the method of Debevec et al. [9], in which the nonlinear function that relates the logarithm of exposure to intensity is obtained. From this g is calculated using the exposure time. Debevec's method gives the log exposure only at certain discrete intensity values, a closed form expression for g is obtained using curve fitting. The nature of the function obtained through curve fitting is,

$$g(R) = a \ln(1 + R/b). \tag{9}$$

where, R is the radiance and a, b are constants obtained through curve fitting (see Fig.1).

2.2 TOTAL VARIATION AS A REGULARIZER

Results of Eq.(8) showed that though the noise is reduced there is substantial smoothing. We propose a TV based prior in order to preserve the edges. The prior is proportional to $exp(-TV(R))$ where $TV(R)$ is the total variation of the radiance map. We also adapt the method of Figueiredo et al. [16] for our nonlinear formulation for faster computation. In [16] the total variation is upper bounded by a quadratic function and the resulting quadratic cost function is solved using conjugate gradient method. The total variation of the radiance R ($TV(R)$) is defined as,

$$TV(R) = \sum_i \sqrt{(\Delta_i^h R)^2 + (\Delta_i^v R)^2} \quad (10)$$

where, Δ_i^h and Δ_i^v corresponds to the horizontal and vertical first order differences. $\Delta_i^h R = r_i - r_j$ and $\Delta_i^v R = r_i - r_k$ where r_j and r_k are the neighbors to left and above, respectively of r_i, the radiance at location i. For the model of Eq.(1), the cost function which is the negative logarithm of aposteriori probability density, with a total variation based prior is,

$$C(R) = \sum_{i=1}^{k} (Y_i - g_i(R))^T (Y_i - g_i(R)) + \lambda TV(R). \quad (11)$$

Since solving this is computationally very demanding, we use the quadratic approximation for TV as proposed in [16],

$$TV(R) \le Q_{TV}(R, R^{(t)}) \underline{\underline{\Delta}} R^T D^T \wedge^{(t)} DR + K(R^{(t)}), \quad (12)$$

where, $R^{(t)}$ denotes the updated value of R at iteration number t. Here D denotes the matrix which when operated on a vector gives the first order horizontal and vertical finite difference of the vector. D is defined as $D = [(D^h)^T (D^v)^T]^T$, where D^h and D^v denote matrices such that $D^h R$ and $D^v R$ are the vectors of all horizontal and vertical first order differences. $\Lambda^{(t)}$is defined as

$$\Lambda^{(t)} = \text{diag}(W^{(t)}, W^{(t)}), \quad (13)$$

where, diag(L) means a diagonal matrix with elements of L as the diagonal and $W^{(t)}$ is a vector whose i^{th} element is

$$w_i^{(t)} = \lambda \left(2\sqrt{\left(\Delta_i^h r^{(t)}\right)^2 + \left(\Delta_i^v r^{(t)}\right)^2} \right)^{-1}, \quad (14)$$

$K(R^{(t)})$ is a constant independent of R, and hence is not considered in the overall cost function. The overall cost function ($C(R)$) is obtained by substituting Eq.(12) in Eq.(11) and neglecting the terms that do not affect the optimization. This gives,

$$C(R) = \sum_{i=1}^{k} (Y_i - g_i(R))^T (Y_i - g_i(R)) + R^T D^T \Lambda^{(t)} DR,$$

$$= R^T D^T \Lambda^{(t)} DR + \sum_{i=1}^{k} (g_i(R)^T g_i(R) - 2g_i(R)^T Y_i) + \sum_{i=1}^{k} Y_i^T Y_i. \quad (15)$$

The method proposed by [16] is for a linear system, since Eq.(15) contains the nonlinear term $g(R)$, we linearize this at $R^{(t)}$, the solution at iteration t, as follows,

$$g(R) = g(R^{(t)}) + \Delta g(R^{(t)})(R - R^{(t)}), \quad (16)$$

where, $\Delta g(.)$ is an $MN \times MN$ diagonal matrix whose diagonal entries are $\partial g(R)/\partial r_i$, $i = 1....MN$ evaluated at $R = R^{(t)}$.

Using Eq.(16) in Eq.(15) and equating the derivative of the cost function to zero, we get

$$[D^T \Lambda^{(t)} D + \sum_{i=1}^{k} A_i^2] R = -\sum_{i=1}^{k} A_i G_i + \sum_{i=1}^{k} A_i^2 R^t + \sum_{i=1}^{k} A_i Y_i, \quad (17)$$

where, $G_i = g_i(R)|R = R^t$ and $A^i = \Delta g_i(R)|R = R^t$. We solve Eq.(17) directly using the conjugate gradient method to obtain the radiance value at iteration $t + 1$. There is an outer loop which is indicated by t, and an inner loop which is the conjugate gradient step.

The optimum radiance is obtained by solving Eq.(17) iteratively. Once the radiance is obtained, it is tone mapped to get the LDR equivalent of the HDR image.

3. JUSTIFICATION FOR USING RADIANCE DOMAIN

Here we justify the reason for doing a simultaneous radiance domain fusion and denoising as opposed to image domain denoising. Conventional denoising methods estimate the intensity that maximizes the aposteriori probability of the image intensity given the noisy observation. We show that the optimum intensity is not same as the intensity obtained by tone mapping the optimum radiance estimate. We do the analysis considering only a single observation, for simplicity and we assume the prior obtained by modeling the image as a GMRF. The extension to TV prior is straight forward as is shown in *Claim* 2.

The model used while estimating intensity is same as that given in Eq.(1) with $g(R)$ replaced by X, for a single observation. While estimating the optimum intensity, the intensity is assumed to be a GMRF, which is the same assumption used in Eq.(7) while estimating the radiance. Since the nature of prior function is the same for the intensity as well as radiance formulations, the corresponding cost functions can be written as in Eq.(18) and Eq.(19), respectively. They differ only in the data term $d(X)$. In both the equations $r(.)$ is same as $U(.)$ of Eq.(4)

$$C_1(X) = d(X) + \lambda_1 r(X). \quad (18)$$

$$C_2(R) = d(g(R)) + \lambda_2 r(R). \quad (19)$$

Let $\hat{X}$ be the intensity that minimizes Eq.(18) and $R_G^{'}$ the corresponding radiance, i.e. $R_G^{'} = g^{-1}(\hat{X})$, and let $\hat{R}_G$ be the radiance that minimizes Eq.(19).

Claim 1: $\hat{X} \ne g(\hat{R}_G)$ = g(R^G)

Proof: We will prove the claim by contradiction. Assume that

$$\hat{X} = g(\hat{R}_G), \quad (20)$$

where, $\hat{X}$ is defined as,

$$\hat{X} = \arg\min_X C_1(X). \quad (21)$$

i.e., $$\nabla d(\hat{X}) + \lambda_1 \nabla_r(\hat{X}) = 0, \quad (22)$$

where, $\nabla d(\hat{X})$ is the gradient of $d(X)$ at $X = \hat{X}$. If $R_G^{'}$ minimizes $C_2(R)$, then $\nabla C_2(R_G^{'}) = 0$, where $\nabla C_2(R)$ is the gradient of $C_2(R)$. From Eq.(19), $\nabla C_2(R)$ is,

$$\nabla C_2(R) = D_g D_d + \lambda_2 \nabla_r(R), \tag{23}$$

where, D_g is a diagonal matrix with the diagonal $\left[\frac{\partial_g(r_1)}{\partial_{r1}}, \ldots, \frac{\partial_g(r_k)}{\partial_{rk}}\right]$ and D_d is the column vector $\left[\frac{\partial d(g(r_1))}{\partial g(r_1)}, \ldots, \frac{\partial d(g(r_k))}{\partial g(r_k)}\right]^{'}$.

Since D_d is essentially the derivative of the function d(.),

$$D_d = \nabla d(X). \tag{24}$$

With $R_G^{'} = g^{-1}(\hat{X})$, the gradient of $C_2(R)$ at $R_G^{'}$ becomes,

$$\nabla C_2(R_G^{'}) = D_g D_d \mid R_G = R_G^{'} + \lambda_2 \nabla_r(R_G^{'}). \tag{25}$$

At $R_G = R_G^{'}, D_d \mid R_G = R_G^{'} = \nabla d(X^{'})$. Using (22)

$$D_d \mid R_G = R_G^{'} = -\lambda_1 \nabla_r(\hat{X}). \tag{26}$$

Let $R_G^{'} = \hat{R}_G$, i.e. $R_G^{'}$ minimizes, $C_2(R)$, then $\nabla C_2(R_G^{'}) = 0$. Using this and Eq.(26) in Eq.(25)

$$D_g \lambda_1 \nabla_r(\hat{X}) = \lambda_2 \nabla_r(R_G^{'}). \tag{27}$$

For the case where r(.) is the smoothness function derived from Gibbs equivalent distribution Eq.(4), gradient of $r(X)$ is of the form AX, where A is a matrix whose entries depend on the neighborhood relation used. Using this in Eq.(27)

$$D_g A\hat{X} = \frac{\lambda_2}{\lambda_1} AR_G^{'}, \tag{28}$$

$$\hat{X} = \frac{\lambda_2}{\lambda_1} A^{-1} D_g^{-1} AR_G^{'}. \tag{29}$$

The relation between $\hat{X}$ and $R_G^{'}$ as suggested by Eq.(29) is not same as $\hat{X} = g(R_G^{'})$. Considering the i^{th} row of Eq.(29)

$$\hat{x}_i = \sum_{k \in N_i \cup i} \alpha k r_i^{'} r_k^{'} \tag{30}$$

where, α_k are constants and N_i is the set of neighbours of i. This leads to a contradiction since, $\hat{x}_i = g(r_i^{'})$ by definition and g(.) is a concave function. In our experiments $g(R_G) = a \ln(1 + R_G/b)$, and Eq.(30) is not of this form. Hence the assumption that $R_G^{'}$ minimizes $C_2(R)$ is not correct, i.e., $R_G^{'} \neq \hat{R}_G$, which proves the claim.

A proof on similar lines can be given when TV based prior is used. With the quadratic upper bound for TV, the cost functions given in Eq.(18) and Eq.(19) get modified as,

$$C_3(X) = \|X - Y\|^2 + X^T D^T \Lambda_X^{(t)} DX, \tag{31}$$

and

$$C_4(R) = \|g(R) - Y\|^2 + R^T D^T \Lambda_R^{(t)} DR, \tag{32}$$

respectively, where the terms are defined as in Eq.(12), with the difference that $\Lambda_X^{(t)}$ is obtained by replacing λ in Eq.(14) by λ_1 and the radiance values r are replaced by the intensity values x and $\Lambda_R^{(t)}$ is similar to Eq.(14) with λ replaced by λ_2 .Let $\hat{X}$ be the intensity that minimizes Eq.(31) and $R_T^{'}$ the corresponding radiance, i.e. $R_T^{'} = g^{-1}(\hat{X})$, and let $\hat{R}_T$ be the radiance that minimizes Eq.(32).

Claim 2: $\hat{X} \neq g(\hat{R}_T)$.

Proof: We will again prove the claim by contradiction, and the method is similar to the previous proof. From Eq.(31), $\hat{X}$ is obtained as,

$$\hat{X} = \left(I + D^T \Lambda_X^{(t)} D\right)^{-1} Y. \tag{33}$$

It may be noted that Eq.(33) has to be solved iteratively and is valid with $\Lambda_X^{(t)}$ evaluated at some particular X value. Taking the derivative of Eq.(32) w.r.t. R, gives

$$\nabla C_4(R) = 2D_g g(R) - 2D_g Y + 2D^T \Lambda_R^{(t)} DR, \tag{34}$$

where, D_g is defined as in Eq.(23). Let, $R_T^{'} = \hat{R}_T$, i.e., $R_T^{'}$ minimizes Eq.(34), then $\nabla C_4(R_T^{'}) = 0$, i.e.

$$D_g \mid R = R_T^{'} g(R_T^{'}) - D_g \mid R = R_T^{'} Y + D^T \Lambda_R^{(t)} DR_T^{'} = 0. \tag{35}$$

Using $R_T^{'} = g^{-1}(\hat{X})$ and Eq.(33) in Eq.(35) gives,

$$D^T \Lambda_R^{(t)} DR_T^{'} = D_g \mid R = R_T^{'} D^T \Lambda_X^{(t)} D\hat{X}, \tag{36}$$

which leads to,

$$R_T^{'} = D_g \mid R = R_T^{'} \left(\Lambda_R^{(t)}\right)^{-1} \Lambda_X^{(t)} \hat{X}. \tag{37}$$

From Eq.(37) it is seen that the relation between $R_T^{'}$ and $\hat{X}$ is not of the form $\hat{X} = g(R_T^{'})$, where g(.) is of the form Eq.(9) which leads to a contradiction. Hence the assumption that $R_T^{'}$ minimizes $C_4(R)$ is not correct, i.e., $R_T^{'} \neq \hat{R}_T$, which proves the claim.

4. RESULTS AND DISCUSSIONS

The first step is to obtain the inverse camera response function from the noisy observations, this function relates the intensity to log exposure. From this, by knowing the exposure time, the function that relates radiance to intensity (g(.)) is obtained. This function has to be estimated for each of the exposure settings. Since only the noisy observations are available, we estimate g(.) in two different ways: 1)using the noisy data and 2)denoise the LDR images and then estimate the function. The results of both for a noise variance (σ^2) of 20 are shown in Fig.1. Since both methods give almost the same estimate for the function, we choose to estimate the function from noisy data directly which needs less computation. A closed form expression for g(.) is obtained through curve fitting using Eq.(9).

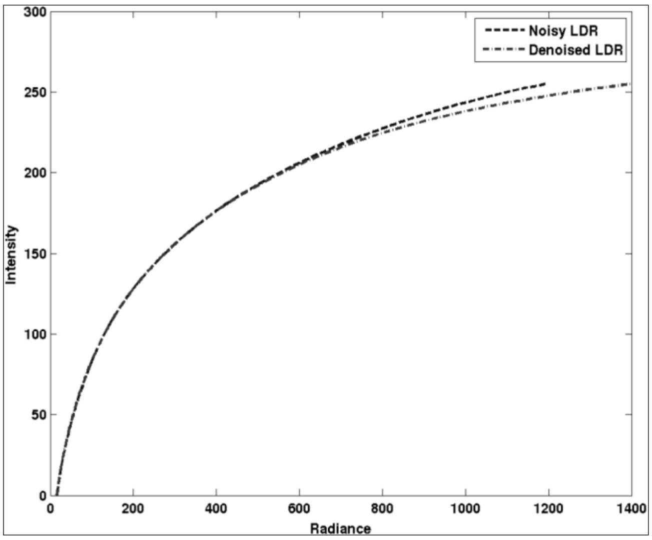


Fig.1. Plot of intensity vs. radiance obtained from noisy and denoised LDR images, noise variance = 20

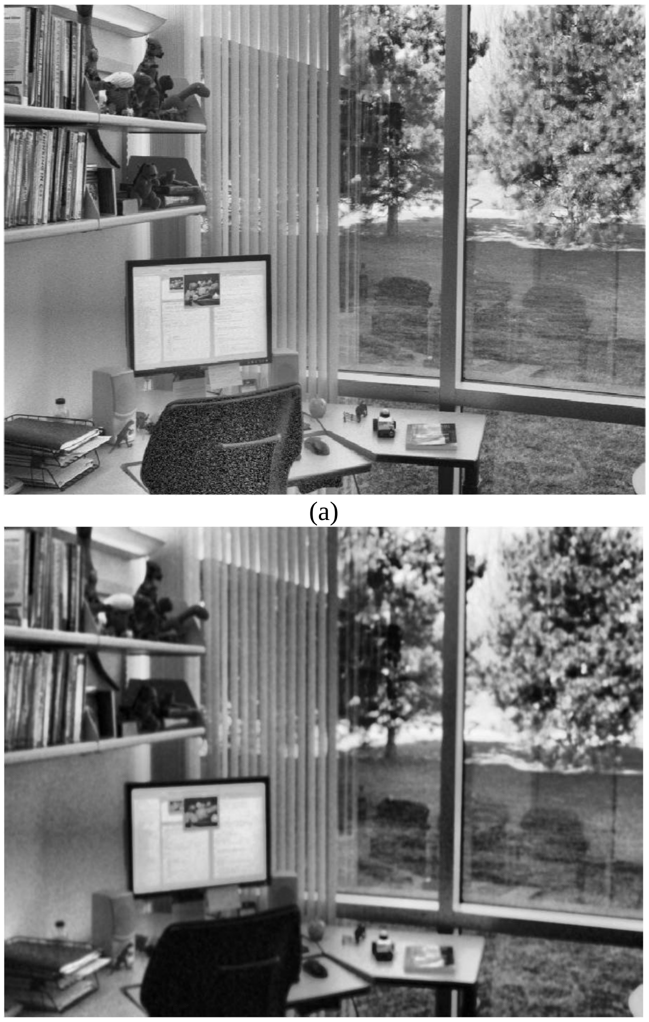
The expression of $g_i(.)$ thus obtained is used in Eq.(7) and Eq.(19) and the optimum radiance is obtained. The number of iterations and regularization parameter were chosen empirically to obtain the best visual quality. The initial condition for the iteration is taken as the average radiance obtained from each of the noisy LDR images. The HDR image obtained from Debevec's method [9] and the two proposed methods are given in Fig.2 for an image corrupted by noise of variance 30. All the images were generated using the same tone mapping function. It is seen from Fig.2(a) that there is a noticeable noise level in the HDR image obtained using Debevec's method, especially where the image is dark as is noticed on the chair. It is also noticed that though noisy, the fine details are preserved in Debevec's method, for example the text visible on the books is readable in the first image. For the GMRF prior (Fig.2(b)) , the smoothing is high which gives the image a blurred appearance, the text on the books is no longer visible, the edges of the window and the window blinds are eroded and other fine details are also blurred, though the noise level has decreased considerably. Analyzing the result of TV regularization (Fig.2(c)) it is seen that this method gives a sharper image, which is expected since the total variation preserves edges. The text is clearly visible, fine details are well preserved and the noise is also reduced considerably.

The second data set (Fig.3) shows an image corrupted by noise of variance 15. It is seen from Fig.3(a) (Debevec's method) that noise is visible on the leaves, which are bright, and also on the top right corner of the image. Using a GMRF prior reduces the noise but as seen from Fig.3(b), there is smoothing which is observed on the rock, and also on the lizard's body where the patches are blurred. This blurring can be observed if the image is zoomed (see Fig.4). From the result of TV regularization shown in Fig.3(c) it is seen that noise is removed considerably and that the edges are also preserved, which gives a sharp low noise image.

We also provide a third data set which shows an image corrupted by a noise of variance 20 (Fig.5). In Fig.5(a) which shows the result of Debevec's method, noise is observed on the wall, table top and on the windows. Using GMRF prior reduces the noise as seen in Fig.5(b), but there is considerable smoothing which can be observed on the objects on the shelf, the tree seen through the window and also on the objects on the table behind the chair. The result of TV regularization (Fig.5(c)), shows that noise is reduced to a large extent and the edges are also well preserved.

5. CONCLUSIONS

In this paper, we have proposed a radiance domain compositing and denoising method for high dynamic range imaging, using GMRF and TV based priors. From the results discussed above it is seen that our method which uses TV based prior gives a less noisy but sharp image, which is of higher quality than the image generated by Debevec's method. In the case of TV based prior, we have adapted the majorize-minimize method of Figueiredo et al. [16] for our nonlinear formulation, which leads to faster convergence. The results were obtained with 3 outer loop iterations and a conjugate gradient loop of less than 20 iterations, with appropriately chosen regularization parameter. The algorithm was implemented in MATLAB running on an Intel core 2 quad CPU, at 2.66 GHz with 4GB RAM. The running time for direct TV and our implementation was 136s and 72s respectively for the second data set (image of size 1632 × 2464), indicating speed up by a factor of two.



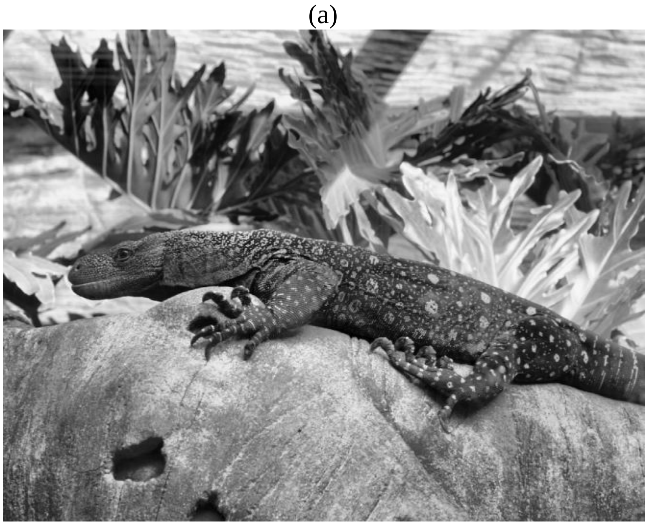
(a)

(b)

(c)

Fig.2. Tone mapped HDR images from noisy (variance 30) LDR images using: (a). Debevec's method (b). GMRF prior (c). TV prior (Data Courtesy: MATLAB Image Processing Toolbox)

(a)

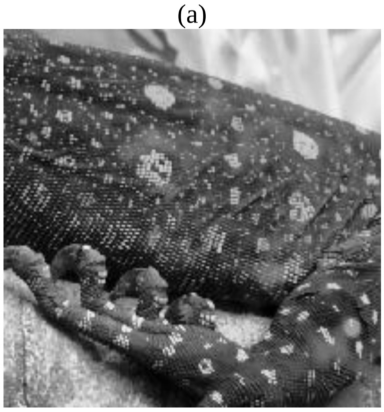


(b)

(c)

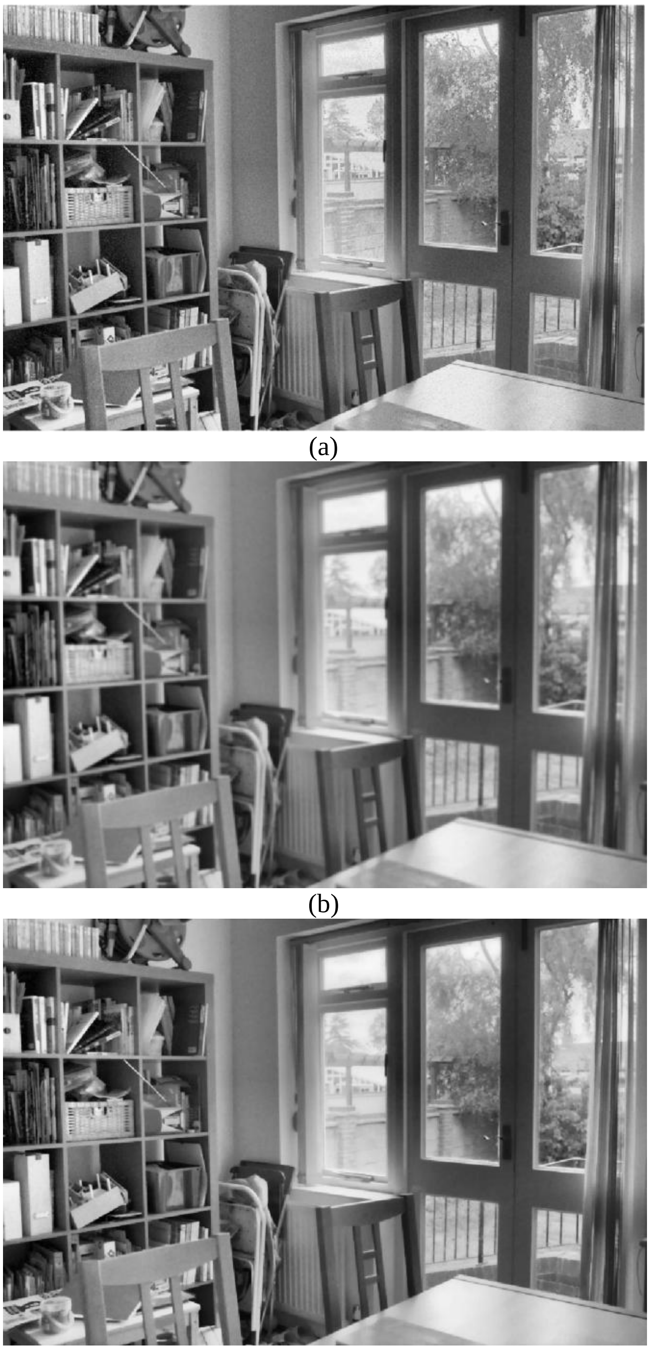
Fig.3. Tone mapped HDR images from noisy (variance 15) LDR images using: (a). Debevec's method (b). GMRF prior (c). TV prior (Data Courtesy: Erik Reinhard, University of Bristol)

(a)



(b)

Fig.4. Zoomed portion of Fig.3, (a). GMRF prior (b). TV prior (Data Courtesy: Erik Reinhard, University of Bristol)



(a)

(b)

(c)

Fig.5. Tone mapped HDR images from noisy (variance 20) LDR images using: (a). Debevec's method (b). GMRF prior (c). TV prior (Data Courtesy: Tom Mertens, Hasselt University)

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