International Journal of Research Studies in Science, Engineering and Technology [IJRSSET]
Volume 1, Issue 4, July 2014, PP 1-9
ISSN 2349-4751 (Print) & ISSN 2349-476X (Online)

A Novel Method for Image Tone Mapping by Local Edge-Preserving Filter

Deepak K,Nithya.E,
Assoc prof

Abstract: *A good efficient method of high resolution image tone mapping is proposed here. filter is proposed for edge-preserving decomposition of an image. Compare to other filter it is different from previous filters in its locally adaptive property. The filtered image contains local means everywhere and preserves local salient edges. Comparisons are made between our filtered result and the results of three other methods. A detailed analysis is also made on the behavior of the filter. A multi scale decomposition with this filter is proposed for manipulating a high dynamic range image, which has three detail layers and one base layer. The multi scale decomposition with the filter addresses three assumptions: the base layer preserves local means everywhere; every scale's salient edges are relatively large gradients in a local window; and all of the nonzero gradient information belongs to the detail layer. An effective function is also proposed for compressing the detail layers. The reproduced image gives a good visualization. Experimental results on real images demonstrate that our algorithm is especially effective at preserving or enhancing local details.*

Keywords: *HDR, LEP, Scaling, Compression*

1. INTRODUCTION

Natural scenes always contain high dynamic range areas in comparison with the limited dynamic range Capabilities of cameras or displays. The dynamic range is defined by the ratio between the maximum and minimum light intensities of the scene. An HDR image is commonly obtained by fusing multi-exposure images. The fused HDR image always exceeds the dynamic range of displays. So some mapping is needed here to compress the intensity distribution of the HDR image. The compression is based on the feature of the human visual system (HVS) that it is less sensitive to the low-frequency components than to the high frequency components. The low-frequency components are compressed while the high-frequency components are retained. Through this reproduction process, we can hardly discern the difference between the artificial image and the real scene. Special considerations are also noted here to avoid artifacts (e.g., halo, the brighter or darker bands around edges). image into an illumination image and a reflectance image. The illumination image is always assumed to be the low frequency component, and the reflectance image corresponds to the high-frequency component. This theory is usually used in enhancing images. And recently, it is also used to reproduce the HDR images due to its dynamic range compression feature. The decomposition process is usually based on a Gaussian filtering to estimate the surround or adaptive illumination in Center/Surround Retine. This causes significant halo artifacts in result images. Later, bilateral filtering is used to replace the Gaussian filtering, and produces much better results. However, it is hard to determine parameters in bilateral filtering, which still suffers halo artifacts. Edge-preserving becomes an important property in filtering design to avoid halo artifacts. This technique decomposes an image into a piecewise smooth base layer and a detail layer. The base layer no longer only contains low frequency band, but it also has salient edges (high frequency). Multi-scale is used here to decompose progressively another detail layer from the last decomposed base layer. In other words, the high-frequency information is progressively decomposed from the original image. There is an important property in the decomposition, which is the residual base layer matches the large-scale shape of the original image signal. The tone mapped images using these edge-preserving filters give state-of-the-art quality, and they are visually appealing. In this paper, we adopt the nice feature of the multi scale edge-preserving decomposition. The salient edges are no longer thought of as large gradients of the whole image, and they are locally adaptive. This is intuitive that one large gradient may not be a salient edge in a larger scale or the whole image. In other words, one small gradient may also be an important edge locally. So, our definition of salient edge is different from. A salient edge is defined as a large gradient globally in, while we define a salient edge as a relatively large gradient locally. Therefore, the decomposition process is different in that a locally salient but small gradient will be decomposed into the base layer. We call our filter local edge-preserving (LEP) filter, and it will efficiently and effectively produce visually pleasing images as will be shown in figures of this paper.

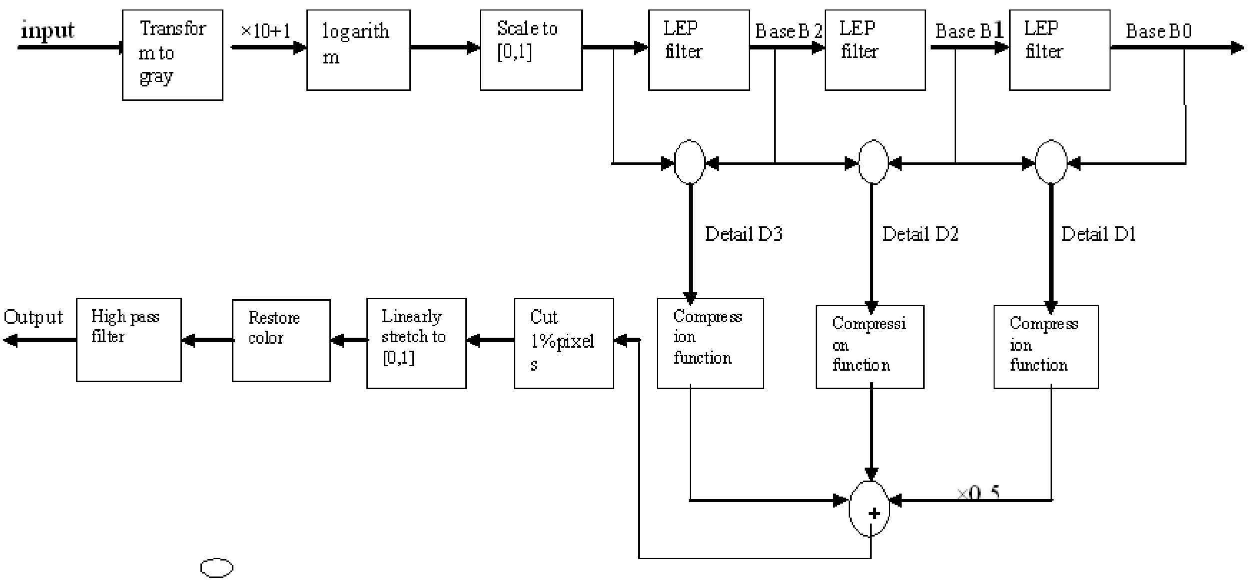
2. PROPOSED ALGORITHM

Local adaptive multi-scale image decomposition has been explored. Here, we propose another approach, which is more efficient than theirs. The assumption that the base layer preserves local means leads to the detail layer oscillating around zero. One commonly used constraint for this assumption is minimizing:

$$\iint_{w}^{0}(I-B)2dxdy,$$

where w stands for the local window, I stands for the image's luminance and B stands for the base layer. This constraint is commonly used in with various interpretations. We explain it here that this constraint satisfies our first assumption. If B is smooth enough in a window that it equals a constant value at every pixel, then minimizing will be done by taking the derivatives to equal zeros at every point, as follows. The results are compared with the results by some recent effective algorithms. The comparisons show that our algorithm is good at compressing the high dynamic range while preserving local tiny details, and the global view is appealing. The process is very efficient for its linear asymptotic time complexity of the image size. We have arbitrarily assumed a linear function between the input and the filtered output in a local window in the filter designing, and then averaged all the output values globally. The linear operations may be a cause of artifacts in results, since they may unsuitably reduce the gradients. It can be seen from that the details near an edge are preserved, which should be smoothed.

3. FUNCTIONAL ARCHITECTURE



When we need to preserve edge information and at the same time preserve the edges. Even when uniform smoothing does not remove the boundaries, it does distort them. This is not acceptable in the context of, for example, medical imaging. An alternative to linear filtering, called anisotropic diffusion, who used a similar nonlinear diffusion processes to model human vision. The motivation for anisotropic diffusion (also called non uniform or variable conductance diffusion) is that a Gaussian smoothed image is a single time slice of the solution to the heat equation, that has the original image as its initial conditions. Thus, the variable conductance can be formulated to limit the smoothing at "edges" in images, as measured by high gradient magnitude, similarly we present our filtered result together with bilateral filter, guided filter and. The input is a synthetic image used in We intentionally set the window radius (if it has) a large value for testing the edge preserving effect. It seems that WLS is the best at preserving edges while smoothing oscillations. Bilateral filter and guided filter are not good at preserving edges. And our LEP seems to rank between them. It can preserve edges, but the smoothing seems not good as WLS. This is just the feature of our LEP that local salient edges are preserved in the filtered based layer. Our filter's advantage is the preserving of local edges. Another advantage of our LEP is that the algorithm's asymptotic time complexity is O(n), independent of the window size. Because the main operation is averaging, it can be implemented by box filters, as reported in these paper.

There are few modules which are used here

- Transform to gray
- Scaling
- LEP filter
- Compression

3.1. Transform to Gray

The image allows you to interactively see the effect of changing a gray level transform function. For each pixel in the image, the pixel intensity, i, is transformed according to the transform function, T[i]. The transform function is the same across the entire image. This is often called a global gray level transform. Effectively we are changing the contrast of the image.

The log transformations can be defined by this formula

$s = c \log(r + 1)$.

Where s and r are the pixel values of the output and the input image and c is a constant. The value 1 is added to each of the pixel value of the input image because if there is a pixel intensity of 0 in the image, then log (0) is equal to infinity. So 1 is added , to make the minimum value at least 1.

During log transformation , the dark pixels in an image are expanded as compare to the higher pixel values. The higher pixel values are kind of compressed in log transformation. This result in following image enhancement.

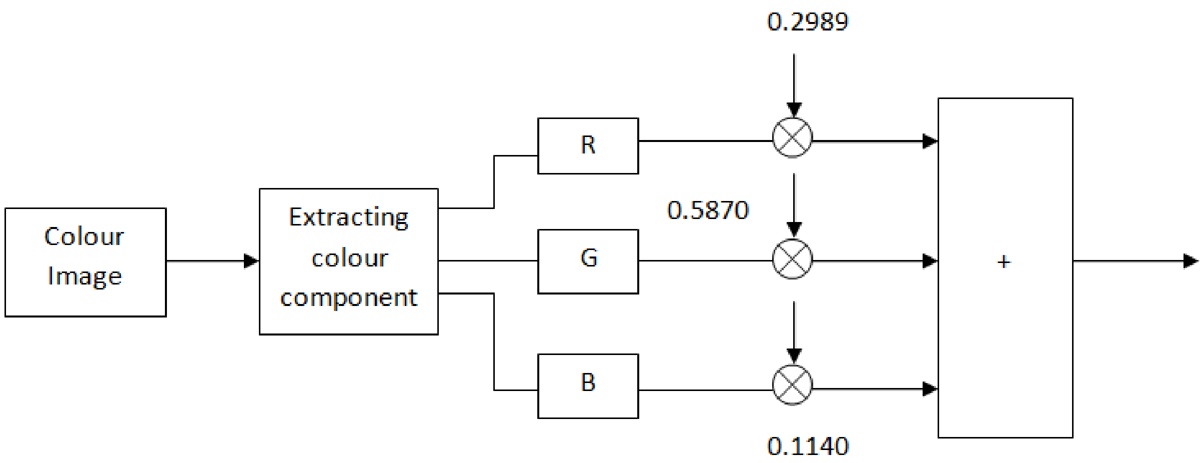


Fig:3.1(a)

3.2. Scaling

Image scaling is the process of resizing a digital image. Scaling is a non-trivial process that involves a trade-off between efficiency, smoothness and sharpness. With bitmap graphics, as the size of an image is reduced or enlarged, the pixels that form the image become increasingly visible, making the image appear "soft" if pixels are averaged, or jagged if not. With vector graphics the trade-off may be in processing power for re-rendering the image, which may be noticeable as slow re-rendering with still graphics, or slower frame rate and frame skipping in computer animation.

Apart from fitting a smaller display area, image size is most commonly decreased (or sub sampled or down sampled) in order to produce thumbnail. Enlarging an image (up sampling or interpolating) is generally common for making smaller imagery fit a bigger screen in fullscreen mode, for example. In "zooming" a bitmap image, it is not possible to discover any more information in the image than already exists, and image quality inevitably suffers. However, there are several methods of increasing the number of pixels that an image contains, which evens out the appearance of the original pixels.

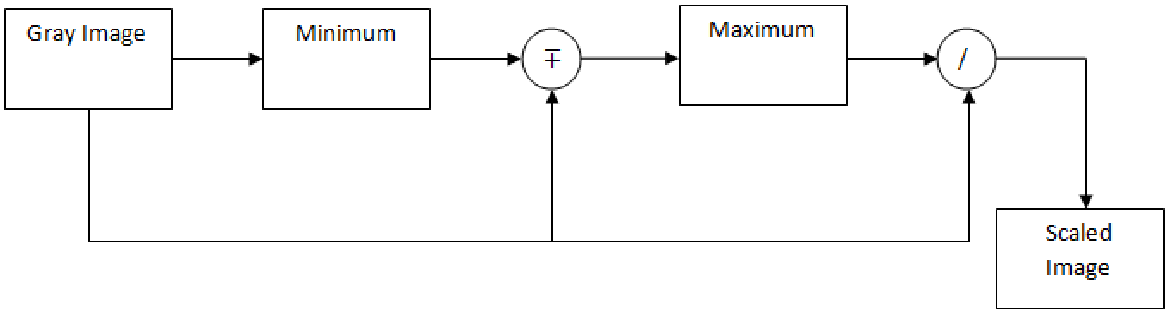


Fig:3.1(b)

3.3. LEP Filtering

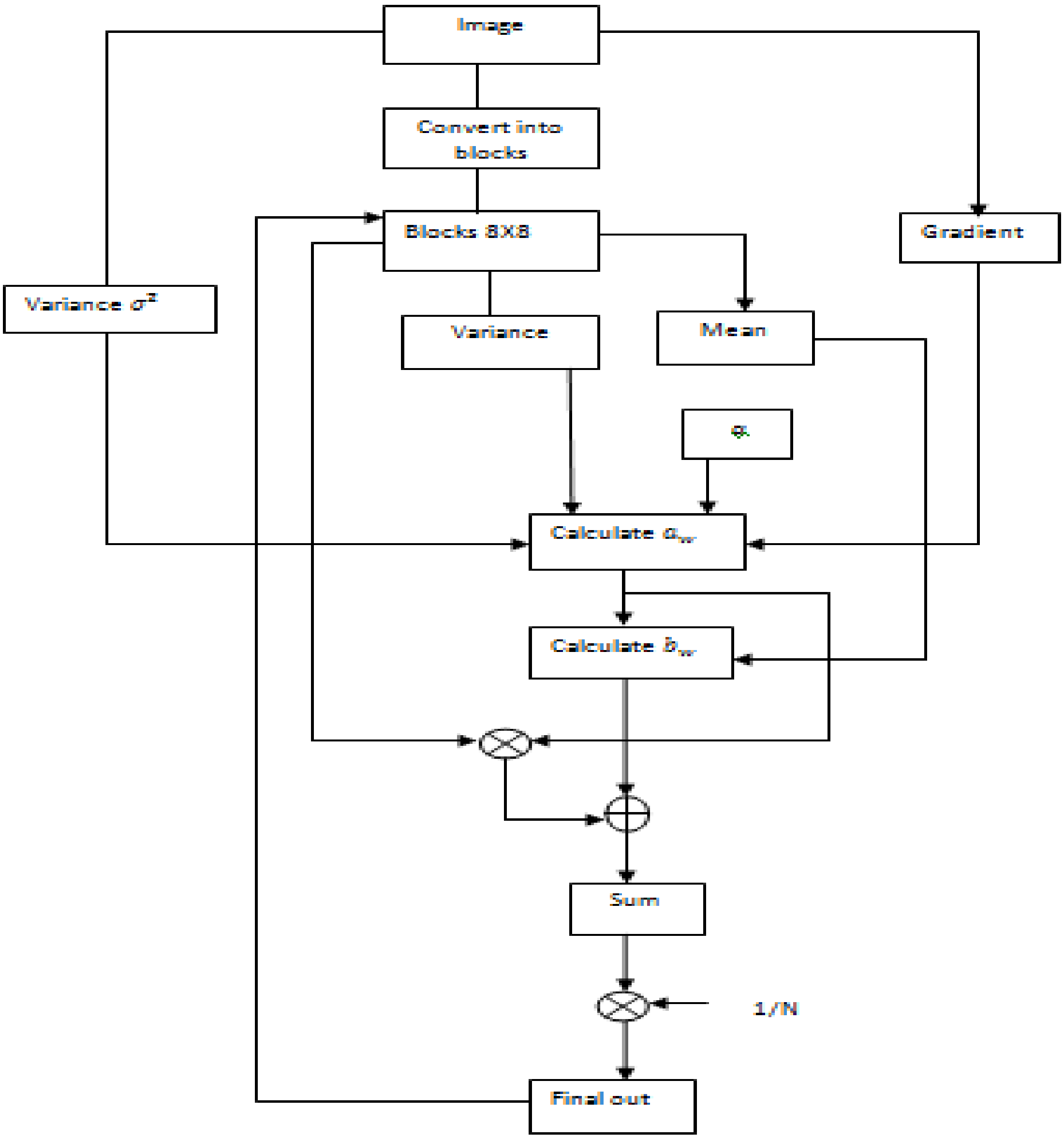


Fig:3.1(c)

An local edge preserving smoothing filter effectively reduces noise levels while preserving fine Structures in data. The behavior of the filter is controlled easily by two control parameters. to adaptively control the behavior of the filter, the control parameter, alpha can be set as a function of the local directional variances. The control parameter, beta can set as a function of all of the directional variances and directional means. The filter includes; a computer means which receives the filter window size, The number of filter directions and input data, adaptive weighting parameter map means which receives the control parameters, alpha, adaptive weighting process means, adaptive combination parameter map means which receives the control parameters, beta, and final compute means which provides the filtered output data.

There are two parameters for LEP: *α_*, *β*. They are relevant to the filter's sensitivity to gradient. More gradients will be treated as salient edges when *α_* or *β* is small. Otherwise, when *α_* or *β* is large, the filtered output will be over smoothed (less gradients will be treated as salient edges). The effect of the parameters for a real image is shown in Fig. 3. Nine results are presented in a matrix with *α_* varying vertically and *β* varying horizontally. The image becomes blurred with the increase of *α_* or *β*, while the details are kept with the decrease of *α_* or *β*. We find values for *α_* = 0.1 and *β* = 1 to always produce satisfactory results, burring details while preserving salient edges.

3.4. Dynamic Range Compression

Since detail layers are oscillating around zero, we seek a function to compress large deviations away from zero and enhance low ones. The compression function should be able to make the deviations at every point as equal as possible. The function should also be convex in order to avoid gradient reversal, and it should be symmetric about zero. Thus it is sigmoid, and we have found one:

$$y = 2 \cdot \arctan(x \cdot 20)/\pi.$$

The arc tangent function varies between $-\pi/2$ and $\pi/2$, so we divide it by $\pi/2$ to compress the range to (0, 1), in which the image pixel values are operated in this study. The multiplier 20 for input shrinks the shape of the arc tangent function, making it changing to flat as quickly as possible. We note that almost all sigmoid functions work well here, but those, whose slopes are too large near zero, may cause artifact enhancement. This function takes in detail layers and puts out the compressed detail layers. The base layer is simply dropped as mentioned before. After the compression process, all the detail layers are summed up to give the result. A linear scaling to the normal range [0, 1] is also needed.

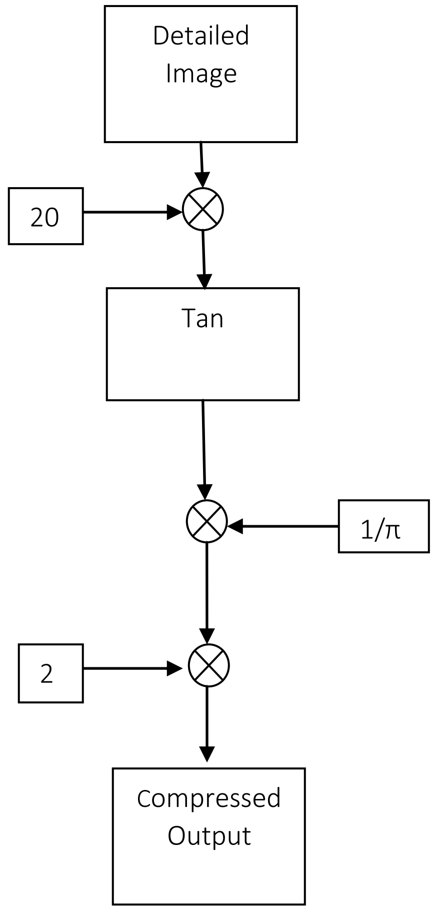


Fig:3.1(d)

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1. Implementation

The input HDR radiance map has to be transformed into a gray image ranging in [0, 1]. We get the luminance simply by averaging the three channels.1 And then the luminance is transformed In to its logarithm domain. This is a typical operation of most methods. The logarithm of luminance approximates the perceived lightness .To sufficiently use the domain of the logarithm function, we arbitrarily magnify the luminance. 10^6 times 2 . It is calculated as follows:

$$L = \ln(\mathrm{Lin} \cdot 10^6 + 1),$$

Where ln() represents the natural logarithm. Finally, the gray image is found by scaling L into range [0, 1]:

$$L' = L / \max(L),$$

We address that the algorithm's performance is not sensitive to the selection of window radius. The only consideration is that the first radius for fine-scale decomposition should be small enough to retain fine details. Various results are shown in for the combinations of the radiuses. Another special operation is after the dynamic range compression. Since we have arbitrarily used the mean after twice iterative decompositions to give the last base layer, the last found detail layer bears high dynamic range, and we divide it by two to halve its range. The result image is composed as.

$$Lout = D_1' \cdot 0.5 + D_2' + D_3'$$

where D_1', D_2', D_3' denote the detail layers after compression by:

Lastly, 1% of pixels are cut at low and high values considering noise and increasing the major pixels' contrasts. Subsequently, the range of Lout is stretched linearly to [0, 1]. This is demonstrated in that the low and high ends of the histogram are occupied by few pixels, thus we cut these pixels to get the stretched the histogram. Concrete diagram of our algorithm is shown as Fig.

Input Image **Output Image**

Table 1. *Quantitative Measure*

Methods	Sharpness	Structural fidility	Quality
Proposed method	**14.0561**	**1.0565**	**1.4216**
Existing method	**11.1135**	**0.9885**	**0.9238**

A variety of HDR radiance maps have been experimented, and results are shown in. The source map of is courtesy of . The source map of is courtesy of . We download all the sources from their Webs shows the comparison between ours and the other three recent algorithms: the method based on the bilateral filter (BLF) the method based on the weighted least squares (WLS) filter by and the method based on local extrema. The result of the BLF (a) suffers halo artifacts while the other three don't. Our result (d) represents more details and seems shaper than the others. For example, we take the close-up images (e-h) in the red rectangles of (a-d),respectively. And one can discern more details in (h), of which the blue poster on the left side of the building, and the painting on the truck are especially clearer than the others.

Table 2. *Quantitative Measure*

Methods	Sharpness	Structural fidility	Quality
Proposed method	**14.1249**	**1.0335**	**1.4133**
Existing method	**16.8930**	**0.9593**	**0.9346**

Comparison of the reproduced HDR images obtained by the same process but using different filters.

Table.2 *Quantitative Measure*

Methods	Sharpness	Structural fidility	Quality
Proposed method	**14**	**1.0595**	**1.2346**
Existing method	**2.8180**	**0.9551**	**0.7732**

We use two objective measures to assess the three results of Fig. 9. One assessment measures image sharpness. An image is sharp means the details are clearly presented. The shaper an image is, the larger the measure is. It is defined as the normalized sum of total gradients.

$$S = \frac{1}{N}\sum |\forall I|$$

where N is the number of pixels in image I . Another assessment method is the recently proposed

objective assessment especially designed for tone mapped images. It combines a multi-scale structural fidelity measure and a measure of image naturalness. The structural fidelity measure is a full-reference assessment based on the structural similarity (SSIM) index, and the naturalness measure is a no-reference assessment based on statistics of good-quality natural images. This method provides a single quality score of an entire image. The combined single quality is represented by 'Quality' in this study. The evaluated results are presented in Table I. It can be deduced that our result is sharper and better than others. we replace our filter with the High pass filter in the proposed process and use the same parameters. The WLS filter is a global optimizer while our LEP filter is locally adaptive. The image of (b) seems clearer than that of (a). In the close ups, the lines of codes on the bright screen and the thin tree branches over the bright blue sky can be discerned more easily in (d) than that in (c). The objective evaluations are shown in Table II. We also take experiment on the famous Blue hills image and present in Fig. 11 in comparisons with other seven effective tone mapping algorithms. Our result (a) preserves details everywhere and looks natural and clean globally. The low value for structural fidelity of our result (Table III) is due to the enhancement effect of the compression function. But the defect is not serious, for the evaluation of structural fidelity is very close to others. And more importantly, the naturalness of our result is the best.

5. CONCLUSION

A good efficient method of high resolution image tone mapping is proposed here. The efficient three assumption for our multi scale edge preserving image decomposition. To derive local edge preserving filter different assumption are used. The proposed algorithms also have connection with the previous algorithms . Only two parameters (except the window radius) are needed for our filter, and they can be always set default values for good results. The filter is responsible of multi-scale coarsening an image while keeping local shape of the signal. The process our filter reproduce HDR images. The recent effective algorithms the results are compared.The process is very efficient for its linear asymptotic time complexity of the image size. We have arbitrarily assumed a linear function between the input and the filtered output in a local window in the filter designing, and then averaged all the output values globally. The linear operations may be a cause of artifacts in results, since they may unsuitably reduce the gradients. It can be seen from that the details near an edge are preserved, which should be smoothed. This may be another source of artifacts near edges. A nonlinear function may be a prospect for avoiding these disadvantages.

The different between the results shows that our algorithm is good at compressing the high dynamic range while preserving local tiny details, and the global view is appealing.

REFERENCES

[1] P. E. Debevec and J. Malik, "Recovering high dynamic range radiance maps from photographs," in Proc. SIGGRAPH, 1997, pp. 369–378.

[2] J. M. DiCarlo and B. A. Wandell, "Rendering high dynamic range images," Proc. SPIE, vol. 3965, pp. 392–401, May 2000

[3] E. Reinhard, M. M. Stark, P. Shirley, and J. A. Ferwerda, "Photographic tone reproduction for digital images," in Proc. SIGGRAPH, 2002, pp. 267–276.

[4] E. H. Land and J. J. McCann, "Lightness and retinex theory," J. Opt. Soc. Amer., vol. 61, no. 1, pp. 1–11, Jan. 1971.

[5] Z. Rahman, D. J. Jobson, and G. A. Woodell, "Retinex processing for automatic image enhancement," J. Electron. Imag., vol. 13, no. 1, pp.100–110, 2004.

[6] S. Battiato, A. Castorina, and M. Mancuso, "High dynamic range imaging for digital still camera: An overview," J. Electron. Imag., vol. 12, no. 3, pp. 459–469, 2003.

[7] D. J. Jobson, Z. Rahman, and G. A. Woodell, "Properties and performance of a center/surround retinex," IEEE Trans. Image Process., vol. 6, no. 3, pp. 451–462, Mar. 1997.

[8] M. Elad, "Retinex by two bilateral filters," in Proc. 5th Int. Conf. Scale Space PDE Methods Comput. Vis., vol. 3459. 2005, pp. 217–229.

[9] Z. Farbman, R. Fattal, D. Lischinski, and R. Szeliski, "Edge-preserving decompositions for multi-scale tone and detail manipulation," ACM Trans. Graph., vol. 27, no. 3, pp. 1–10, Aug. 2008.

[10] K. Subr, C. Soler, and F. Durand, "Edge-preserving multiscale image decomposition based on local extrema," ACM Trans. Graph., vol. 28, no. 5, pp. 147–155, Dec. 2009.

[11] R. Kimmel, M. Elad, D. Shaked, R. Keshet, and I. Sobel, "A variational framework for retinex," Int. J. Comput. Vis., vol. 52, no. 1, pp. 7–23, 2003.

AUTHORS' BIOGRAPHY

Deepak K holds BE degree In Information Science and Engineering From the Visvesvaraya Technological university, Belgaum, in 2011.He is currently pursuing in his Master degree in Computer Science and engineering from the same University.From Dr AIT Bangalore. He is having area of interest in the field of Digital image processing and Computer Networks.

Nithya E holds BE degree In Computer Science and Engineering from the Visvesvaraya Technological University, Belgaum, in 1995. He received his Master degree in Computer Science and Engineering in the same university, in 2002. He is currently pursuing his PhD degree in Digital image processing in the same university. Presently, He is working as Associate Professor in the dept. of computer science in Dr. AIT, Bangalore. He is having area of interest in the field of Digital image Processing.