Local Edge Preserving Multiscale Decomposition for High Dynamic Range Video Tone Mapping

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Abstract: - A Local Edge Preserving filter is proposed for Edge preserving decomposition of a video. It is different from other filters. The filtered video contains local means everywhere and preserves local salient edges. A multiscale decomposition with this filter is proposed for manipulating a high dynamic range video, which has three detail layers and one base layer. The multiscale decomposition with the filter addresses three assumptions: 1) The base layers preserves local means everywhere, 2) Every scale's salient edges are relatively large gradients in a local window; 3) all of the nonzero gradient information belongs to the detail layer. An effective function is also proposed for compressing the detail layers. The reproduced video gives a good visualization. Experimental results on real video demonstrate that our algorithm is especially effective at preserving local details.

I.INTRODUCTION

High Dynamic Range

The 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. High dynamic range image is commonly obtained by fusing multi-exposure images. The fused HDR image always exceeds the dynamic range of displays. LEP is an image processing technique that smooth away textures while retaining sharp edges. We need to preserve edge information and at the same time preserve the edges. . So some mapping is needed. Mapping is performed to map one set of colours into another. Here to compress the intensity distribution of the HDR image. The low-frequency components are compressed while the high-frequency components are retained. Through this reproduction process, it can hardly discern the difference between the artificial image and the real scene, and also not avoid artifacts (e.g., halo, the brighter or darker bands around edges). It simulates and decomposes an image into an illumination image and a reflectance image.

Illumination

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 Centre/Surround Retinex. 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).

Multiscale Decomposition

Multi-scale is used here to decompose progressively another detail layer from the last decomposed base layer. 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 Farbman's. 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.

Local Edge Preserving Filter

The local edge-preserving (LEP) filter and it will efficiently and effectively produce visually pleasing images as will be shown in figures of this paper. A salient edge is defined as a large gradient globally in, while we define a salient edge as a relatively large gradient locally.

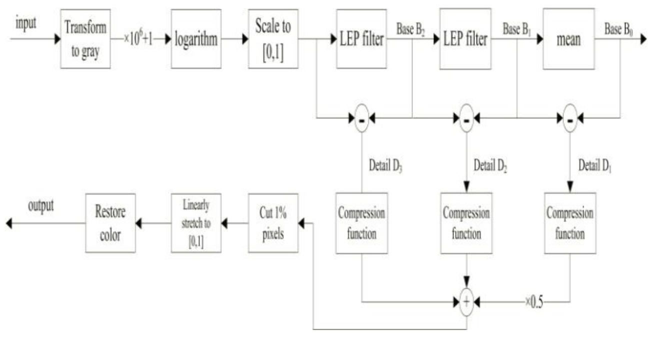

Fig.1.1 Local Edge Preserving Filter

II. ALGORITHM

A.Logarithmic Function

The camera as the product of the illumination *L* and the reflectance *R*. If a logarithm is applied, a summation will generate

$$\text{Log}\,(I) = \log\,(L) + \log(R) \qquad (1)$$

The illumination varies slowly in the scene, but its high dynamic range, while the reflectance varies quickly but its dynamic range is low, our aim is to separate the illumination then compress the dynamic range and recompose the image.

Edge-preserving filtering slightly changes the decomposition problem. It views an image as a base layer *B* (a piecewise smooth image except salient edges) plus a detail layer *D*:

$$I = B + D \qquad (2)$$

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 and then the luminance is transformed into 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:

$$L = \ln(Lin \cdot 10^6 + 1 \qquad (3)$$

Note the standard luminance for RGB color spaces is calculated as 0.2126*R* + 0.7152*G* + 0.0722*B*. For efficiency, the weights are set equal in this study, and the color restoration will also be done equally in every channel.

B. Local Edge-Preserving Filter

The local energy function gets from the above analysis. It satisfies the first and second assumptions in the problem statement. We will find a way to get an optimal solution efficiently. The discrete form is given below:

$$\sum_{i\in w}(I_i - B_i)^2 + \frac{\alpha'}{|\nabla I_i|^{\beta}}|\nabla B_i|^2. \qquad (4)$$

The above energy function can be iteratively minimized to get a numerical solution using the Normalized Steepest Descent (NSD) method. In order to facilitate the solution, we intuitively suppose that *B* has a linear dependence with *I* in a local window, since pixels are highly correlated locally. We thus propose this local approximation of *B* as:

$$Bi = awIi + bw,\ i \in w \qquad (5)$$

where *aw* and *bw* are constant coefficients in the window *w*.

$$\sum_{i\in w}(I_i - a_w I_i - b_w)^2 + \alpha'|\nabla I_i|^{2-\beta}\cdot a_w^2. \qquad (6)$$

The formula is much like the cost function in except the coefficient (α_$|\nabla Ii$ |2−β) between the two constraints.

Ours is adaptive to the gradient while theirs is a set parameter. To see later that our adaptive coefficient will preserve edges while theirs won't. Now the optimal problem becomes a parameter estimating problem. The minimum of can be found by setting the partial derivative of each parameter to zero. This linear least squares' solution is:

$$\begin{cases} a_w = \dfrac{\sigma_w^2}{\sigma_w^2 + \frac{1}{N}\cdot\alpha'\cdot\sum_{i\in w}|\nabla I_i|^{2-\beta}} \\ b_w = \bar{I}_w - a_w \bar{I}_w, \end{cases} \qquad (7)$$

Where σ *2w* is the variance of *I* in the window *w* and ¯*Iw*is the mean of *I* in *w*.

$$\sum_{i\in w}|\nabla I_i|^{2-\beta} = \frac{1}{N}\cdot\sum_{i\in w}|\nabla I_i| \qquad (8)$$

If $\alpha = \beta = 1$, then 1/*N*· α represents the average of the gradients in *w*. It can be easily deduced that *aw* is always less than 1, and the contrasts of the output of equation will always be compressed. In other words, *B* is a smoothed version of *I*.

Each window contains *N* pixels, and each pixel is involved in *N* windows. For every window, there is a set of *aw*, *bw*, and then, the filtered output *Bi* of has *N* different values. The values should be weighted averaged together to retain correct results and diminish distorted ones. However, the weights are hard to figure out, so we simply get the mean of all the *N* values of *Bi*.

If a local window is identified by its central pixel, we change *ak*, *bk* for *aw*, *bw* and *k* denotes the central pixel's location. We get our LEP output as:

$$B_i^l = \frac{1}{N}\sum_{k\in w}(a_k I_i + b_k) = \bar{a}_i I_i + \bar{b}_i, \quad i \in \Omega,$$

(9)

Where Ω represents the area of the image, and aiIi the average of the *ak*in the neighbourhood window and the same with bi

C.Multiscale Decomposition

The third assumption in the problem statement by a multi-scale decomposition (the base layer should only contain zero gradients). A single LEP operating on original image will give a base layer and a detail layer. The base layer preserves local means and local salient edges. The detail layer contains oscillating signal around zero. Iteratively applying LEP to the base layer will generate a multi-scale decomposition. While iterating, the local window is increasing,

Let *LEPl* denote the filter function, and *l* is the scale level, which also represents different local window radii at each filtering level. Then a sequence of progressively coarser versions of image *I* will be:

$Bl-1 = LEPl\ (Bl\ ),\ for\ l = n, . . . , 2, \quad and \quad Bn= I.$ (10)

The detail layers will get as:

$Dl = Bl- Bl-1$, for $l = n . . . 2$. (11)

In order to make the base layer contain only zero gradients, we get the mean of the base layer $B1$ as the last base layer

$B0$: $B0 = Mean\ (B1)$. And then,

$D1 = B1 - B0$. (12)

In this study, we decompose every image into three detail layers and one base layer ($n = 3$).We think this decomposition style addresses a basic idea that one decomposition for the fine scale, one for the medium scale, and one for the whole image's scale. The process can be expressed by:

$I = B0 + D1 + D2 + D3$. (13)

The process is that the salient edges are progressively decomposed into the detail layers.

D. DYNAMIC RANGE CONVERSION

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.

This function to avoid gradient reversal, and it should be symmetric about zero. Thus it is sigmoid function,

$y = 2 \cdot \arctan(x \cdot 20)/\pi$. (14)

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 (e.g., some power functions).

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

III. RESULT

One assessment measures image sharpness. An image is sharp means the details are clearly presented. The sharper an image is, the larger the measure. It is defined as the normalized sum of total gradients:

$S=1/N\ |\nabla I|$ (15)

Where N is the number of pixels in image. 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.

Fig.3.1 (a) Input Video image

Fig.3.1 (b) LEP Filter image

Fig.3.1 The reproduced HDR images obtained (a) input video. (b) LEP filters video

COMPARISON TABLE:

Image	Sharpness	Naturalness	Structural fidelity	Quality
WLS	11.0498	0.7464	0.9400	0.9392
LEP	16.0674	0.7339	0.9489	0.9400

Our algorithm bears asymptotic time complexity of O(n) as mentioned Matlab codes take about 1.2 seconds on a PC with Intel Core i73.4 GHz CPU and RAM 8GB for processing a mega pixel image.

IV. CONCLUSION

Multiscale edge-preserving image decomposition has present three assumptions. A local edge preserving filter has been derived from the assumptions. And we have also explored the connection with 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. Our filter is capable of multi-scale coarsening an image while keeping local shape of the signal. We have also presented a process with our filter to reproduce HDR images. The results are compared with the results by some recent. Video enhancement is one of the most important and difficult components in video research. The aim of video enhancement is to improve the visual appearance of the video, or to provide a "better" transform representation for future automated video processing, such as analysis, detection, segmentation, recognition, surveillance, traffic, criminal justice systems. This assumption can be valid in many scenarios where moving subjects more details and integrated information from the enhanced image. The increasing use of night operations requires more details and integrated information from the enhanced image.

However, low quality video of most surveillance cameras is not satisfied and difficult to understand because they lack surrounding scene context due to poor illumination. In this paper, present a practical system for enhancing the quality of Low Dynamic Range (LDR) videos using High Dynamic Range (HDR) background images.

V. REFERENCES

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