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GLOBAL EDGE-PRESERVING MULTISCALE DECOMPOSITION FOR HIGH DYNAMIC RANGE IMAGE

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Abstract: High Dynamic Range (HDR) imaging is an area of increasing importance of display devices still has Limited Dynamic Range (LDR). Multiscale Decomposition image processing techniques have a reputation of causing halo artifacts when used for range compression. The synthesized Standard Dynamic Range (SDR) image contains much more scene details than any of the captured SDR image. The edge-preserving image decompositions assume image detail to be low contrast variation. This paper proposes a new method of balanced analysis-mixture filters applies with local gain control to the sub-bands systems for decomposing and reconstructing images. The Gradient-domain based algorithm on the properties of HVS for high dynamic range compression. Experimental results on real images demonstrate that our algorithm is especially effective at preserving or enhancing local details.

Keywords:-Edge-preserving filter, halo artifacts, image decomposition, sub band systems.

I. 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 [1]. 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 [2], [3]. 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).

E. Land and McCann proposed the Retinex theory [4] in 1971. It simulates the feature of HVS and decomposes an 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 [5]. And recently, it is also used to reproduce the HDR images due to its dynamic range compression feature [6]. The decomposition process is usually based on a Gaussian filtering to estimate the surround or adaptive illumination in Center/Surround Retinex [7]. This causes significant halo artifacts in result images [8]. 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 [9].

The difference between the luminance of a point and the average luminance of its surrounding points is visible for humans; we term the difference as the visible contrast. In the proposed approach, we use visible contrast and gradient of the whole scene to describe scene details. Given an SDR capture device, the scene luminance is recorded under a specific exposure level as the image luminance, which is determined by the response function of the film or the charge-coupled device.

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 [9], [10]. 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.

II. RELATED WORK

The classic Retinex theory models the light reaching the camera as the product of the illumination L and the reflectance R. If a logarithm is applied, a summation will generate

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$$\log(I) = \log(L) + \log(R) \qquad (1)$$

The illumination varies slowly in the scene, but it bears high dynamic range, while the reflectance varies quickly but its dynamic range is low. The main idea here is to firstly separate the illumination, then compress the dynamic range, and lastly recompose the image.The separation problem is in general ill-posed. Many low-pass filters to estimate the illumination failed in causing artifacts in images. R. Kimmel et al. [11] proposed a mathematically well-posed variational approach to solve this problem and got visually pleasing results. Its energy function reads:

$$\iint (|\nabla L|^2 + \alpha(L-1)^2 + \beta|\nabla(L-I)|^2)dxdy \quad (2)$$
$$\text{subject to } L \geq I,$$

Where α and β are free weighting parameters.

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:

$$I = B + D \quad (3)$$

This is still ill-posed in how a salient edge can be defined. An energy function can also be proposed here to get better results. It was reported by Z. Farbman et al [9]:

$$\iint \left((B-I)^2 + \lambda \left(ax(I) \left(\frac{\partial B}{\partial x}\right)^2 + ay(I) \left(\frac{\partial B}{\partial y}\right)^2 \right) \right) dxdy \; (4)$$

where αx and αy are image information dependent co-efficients and λ is a free weighting parameter. G. Guarnieri et al. [12] proposed a similar approach based on Retinex theory with edge-preserving effect. It is only different in the constraint that the illumination is larger or equal to the received lightness:

$$\iint (\omega|\nabla L|^2 + (L-I)^2)\, dxdy \qquad (5)$$

$$subject\ to: L \geq I,$$

where ω is a space-varying coefficient.The coefficient functions α in (4) and ω in (5) imply the intuitive constraint that the larger the gradient of original information, the more likely it should be decomposed into the base layer. Minimizing the energy function above will get an optimal base layer solution, which smoothes oscillating details but preserves salient edges, and more importantly, it looks like the original image. The idea that an image can be decomposed into a base layer and a detail layer. The base layer is assumed to preserve local means, and then the details are oscillations around zero. Since it is hard to discern which gradient information belongs to base layer and, which belongs to detail layer, we assume that all the nonzero gradient information belongs to the detail layer. And then according to the previous assumption, the base layer should be the mean of the whole image. The base layer only contains zero gradient information. These assumptions seem useless, because a single decomposition makes no difference to the original image. As a result, a multi-scale decomposition is applied. That is an image can be decomposed into a base layer and multiple detail layers: $I = B_0 + D_1 + D_2 + \cdots + D_n \quad (6)$

The base layer B_0 is plain with no gradient, and the cumulative sum of base layer and detail layers is the next scale's base layer, which contains the salient edges and the local means everywhere.

III. PROPOSED SYSTEM

This paper proposes a Gradient-domain based Multiscale putrefaction edge-preserving using compressing high dynamic range images with Haar subband system approach to preserving the edges and correction for images corrupted with colour features. Analysis-Mixture filter bank that extract features with increasing image contrast as successive layers of detail information. As a result, they are unable to distinguish between high contrast, fine-scale features and edges of similar contrast that are to be preserved.

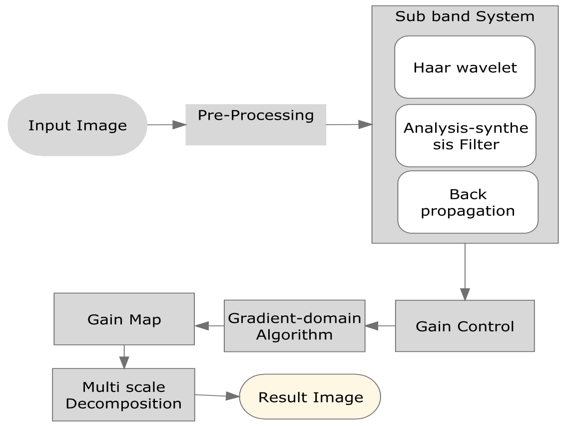

Fig 1: Proposed System

A.HAAR Wavelet Sub-Band System

In mathematics, the Haar wavelet is a certain sequence of rescaled "square-shaped" functions which together form a wavelet family or basis. Wavelet analysis is similar to Fourier analysis in that it allows a target function over an interval to be represented in terms of an orthonormal function basis. The Haar sequence is now recognised as the first known wavelet basis and extensively used as a teaching example in the theory of wavelets. The compression technique of Haar wavelet sub band system is splitting the image into 2-D wavelet stage. In this process, the edges are populated into 4 levels of Haar wavelet functions like (LL, LH, HL and HH). The Gaussian filter function is used to help of image smoothness creation. With the help of filter function, color values are boosting and control the overlapping pixels are avoided.

For a 2-D transform, we can filter along the rows, producing two sub-images each about half the size of the

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original. The heights are the same as the original, but the sub-images have half the width. We then filter these sub-images with low and high-pass filters along the columns. This produces two more sub-images each, for a total of four sub-images. This process is called decomposition or analysis. We label the resulting sub-images from an iteration (called an octave) of the DWT as LL (the approximation), LH (horizontal details), HL (vertical details), and HH (diagonal details), according to the filters used to generate the sub-image.

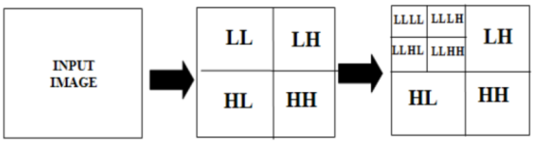

Fig 2: 2-D Haar DWT

B. Analysis – mixture Filter

Analysis-mixture filter banks are often implemented with hierarchical sub sampling, leading to a pyramid. Wavelets and Quadrature Mirror Filters (QMFs) are often used this way, in which case they yield orthogonal transforms [16], [17]. The Laplacian pyramid of a sub sampled system with analysis and mixture filters. Note, however, that it is not symmetrical. The analysis filters are band pass, and the mixture filters are low pass. Thus the mixture filters can remove high frequency artifacts introduced by nonlinear processing, but not low frequency artifacts. It is possible to use the Laplacian pyramid architecture without sub sampling, which reduces aliasing effects, but the asymmetry remains. When nonlinearities introduce distortions that show up in low frequencies, the mixture filters cannot remove them. In spite of these problems, we can get fairly good results with the Laplacian pyramid when we compute smooth gain maps.

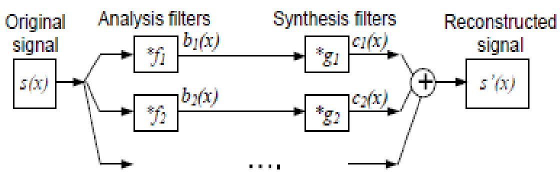

Fig 3: An analysis-mixture sub band system.

C. Gain Direct

A smooth gain map to control the strength of the sub band signals. For ideas on creating this map, it is interesting to consider the use of gain control. A gain direct as a mechanism known as "contrast gain direct" or "contrast normalization" [18]. The gain direct varies from point to point depending on the activity, so a gain map in register with the sub band image. This is analogous to gain map applied to the gradient image.

Neurons have a low dynamic range, and they are noisy, so it is important to keep them within an optimal operating range whenever possible. The first type of automatic gain control happens at the retina, where the photoreceptors rapidly adapt to the ambient light level. For our purposes this process can be crudely modelled as taking the log of the input intensity [19].

The Gaussian filter (Low pass filter) is one very important task is to remove white noise, all the while maintaining significant edges. This can be a contradictory task - white noise exists at all frequencies equally, while edges exist in the high frequency range. (Sudden changes in spatial signals). In traditional noise removal via filtering, a signal is low pass filtered, which means that high frequency components in your signal are completely removed.

The Gaussian 2-D distribution as follows,

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (7)$$

where σ is the standard deviation of the distribution.

In building gain maps for range compression, we first construct an activity map from local filter responses. Since the responses can be positive or negative, we take the absolute value. We then pool over a neighbourhood with a simple blur. The activity map is then converted to a gain map, which has lower gain in regions of high activity.

D. Gain Map

The matching of local sub band gains depends on accidents of image statistics: it is usually the case that high activity in one band is spatially correlated with high activity in adjacent bands. To modify the low frequency sub bands with a gain map that contains a lot of high frequency detail, or vice versa, but due to the symmetric analysis mixture sub band architecture, modified sub bands are post-filtered by the mixture filter bank and therefore all modifications are confined within the sub-bands.

The matching of local sub band gains depends on accidents of image statistics: it is usually the case that high activity in one band is spatially correlated with high activity in adjacent bands.

This gain map is then used to modify all the sub bands, and a scale-related constant η_i is used to control to what extent different frequencies are modified:

$$GM_i'(x,y) = \eta iGC(x,y) \times SBP(x,y) \ldots\ldots (8)$$

Where, GM as Gain Map, GC as Gain control and SBP as Haar wavelet Sub band pyramid parts.

IV. RESULTS

For comparing color images we first convert RGB to the HSV space. The value (V) is then run through the comparing loop and a compressed V is obtained when the

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iterations stop. This compressed V is combined with the original hue (H) and the original saturation divided by a factor, and converted back to RGB to get the compressed color image. This is the same as what we did for color HDR image compression. Similarly when we're going to expand a compressed color image up to one-step range expansion is done on its V channel. The saturation is multiplied by the same the hue is kept the same, and they are combined with the expanded V to get the HDR color image back.

The comparison between Analysis-mixture filter and the other three recent algorithms: the method based on the BiLateral Filter (BLF) by Durand and Dorsey [15], the method based on the Weighted Least Squares (WLS) filter by Z. Farbman et al. [9], and the method based on local extrema by K. Subr et al. [10] and the method based on BLF and Local Edge-Preserving (LEP) filter. The result of the Multiscale Haar Subband Edge-Preserving (MHSEP) method result represents more details and seems shaper than the others. The two objective measures to assess the four results. One assessment measures image Peak Signal Noise Ratio (PSNR). An image is noise means the details are clearly presented.

The test image is matched with database to identify high frequency regions. The PSNR fraction measure of quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression.

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

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \quad (9)$$

Table 1: Peak Signal Noise Ratio for different methods Comparison

Images	WLS filter	LEP filter	Gradient filter
Home	49.56	43.036	51.94
Child	46.88	46.23	50.65
Computer	40.87	46.068	51.25

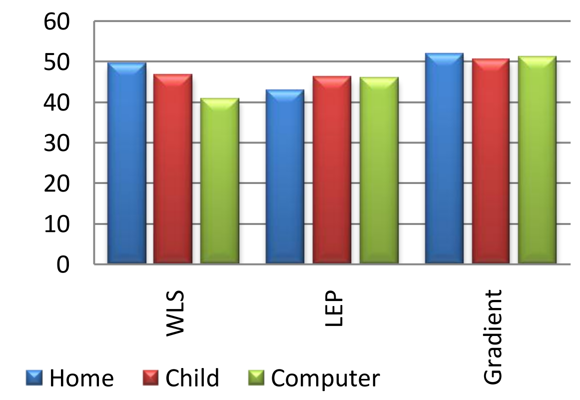

Figure 1: PSNR CALCULATION

The 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.

Table 2: Structural Similarity Ratio for different methods Comparison

Images	WLS filter	LEP Filter	Gradient filter
Home	0.9751	0.9766	0.99927
Child	0.9392	0.9400	0.99993
Computer	0.9327	0.9653	0.99971

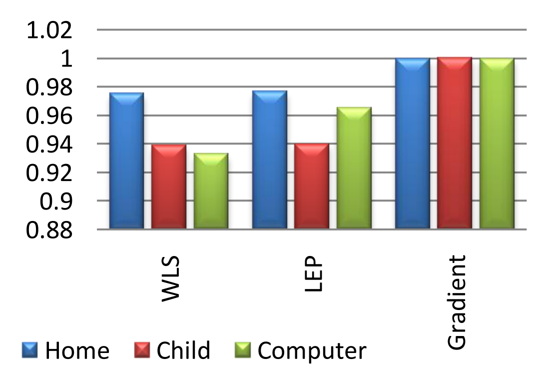

Figure 2: SSIM CALCULATION

Table 3: Gradient Domain Time (In seconds)

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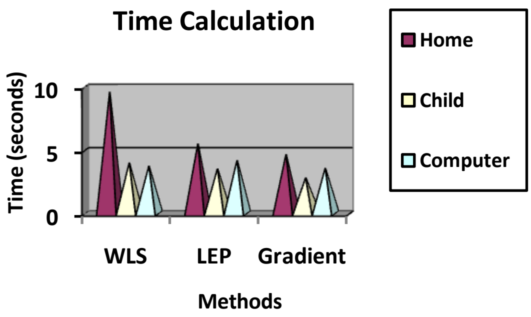
Images	WLS filter	LEP filter	Gradient filter
Home	9.62 sec	5.52 sec	4.688 sec
Child	4.02 sec	3.55 sec	2.844 sec
Computer	3.77 sec	4.22 sec	3.594 sec



V. CONCLUSION

This paper has focused on Gradient-domain based Edge-Preserving Images with Haar Subband Architectures has been developed successfully and the system is tested accurately with all testing methods. Since the project is heavily used to view the detail about image edge preserving and concerned with the color features. This project is highly concerned in the organization and it has been successfully implemented. The analysis-mixture sub band architectures and smooth gain control, gives good range compression without disturbing halos. We describe some simple implementations of sub band range compression, and show that the results are competitive with the leading techniques. A Gradient-domain algorithm is to smooth an input image. By recursively performing the smoothing with extrema detection at single scales, we performed a decomposition of the input image into multiple-scale layers of detail and a coarse residual.

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BIOGRAPHIES

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