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Exposure Fusion in the Non-Sub-sampled Contourlet Domain

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ABSTRACT
Majority of the work, on exposure fusion, for the HDR images, deals with approaches for fusion in the spatial domain. Exposure fusion in the transform domain has been dealt with sparsely in the literature. NSCT provides appropriate markers for identifying weak edges and fine textures, as weak edges and fine textures are lost whenever an under or an over exposure takes place and to allocate proper weights to the pixels before fusing them.
Keywords – exposure, fusion, spatial, textures, transform.

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I. INTRODUCTION

Only one byte per pixel is used in majority of the images to represent each of the R, G and the B components. This gives just 256 values for each pixel. The general configuration of an indoor scene with a window is quite common as in [1]. This leads to both bright and dark areas in the same scene as shown in the fig. [1].

Fig [1]: Set of 4 Multiple Exposure Images of the House. (Images Courtesy Tom Mertens: University of Hasselt)

Taking multiple images with different exposure settings and combining them with some fusion rule is a solution to this problem. An operation called tone-mapping is needed to convert the combined High Dynamic Range Image into the visible spectrum that can be made to display on the currently available display devices. Hence the fusion of multi-exposure images has attracted a lot of attention. Tone-mapping is not without its drawbacks as listed in [1]. Mertens et.al. [1] have arrived at an algorithm called as 'exposure-fusion', which combines the multiple-exposure images to a single image based on certain parameters viz. the 'Contrast', 'Saturation' and the 'Well-exposedness'. In the NSCT based transform based approach that is proposed there is no need to know the camera response function and the camera settings.

All the current approaches for combining the multi-exposure images are mainly in the spatial domain, exposure fusion provides a Low-Dynamic range solution to the High Dynamic range imaging problem as in [2]. The transform domain based approach for exposure-fusion has been dealt with sparsely in the literature on the subject.

The work focuses on a NSCT (Non-sub-sampled Contourlet Domain) based transform domain approach for exposure-fusion. The reasons for the selection and the results generated are discussed in the further sections. A brief comparison has been presented to the various other transform domain based approaches. This work assumes that the input images are perfectly registered. Briefly speaking the work exploits the Non-Sub-Sampled nature and the directional coefficients obtained in the NSCT domain.

II. ABOUT HDR

High dynamic range (HDR) imaging is used to acquire the full dynamic range of a scene with a camera of limited dynamic range. To this end, an exposure set of the scene is acquired, followed by the linearization of each image with the inverse camera response function (CRF), which needs to be measured or estimated. Subsequently, the images are combined into one HDR image. There are many weighting function specified for this combination. Naturally, each individual image is afflicted with noise from the acquisition process. The HDR image obtained has a higher SNR than the acquired images as a consequence of the weighted averaging during reconstruction. Exposure-Fusion as developed by Tom-Mertens et.al. [1], discusses the fusion of the multiple exposure images based on the quality parameters such as the Saturation, Contrast and Well-exposedness. Weights could be assigned to these parameters in the algorithm. The readers are further asked to refer [1] for more details on the Exposure Fusion. The Exposure Fusion algorithm involves the decomposition of the image using the Laplacian Pyramid and the weight maps obtained using the Gaussian Pyramid. This was introduced for reasons mentioned in the reference quoted in [1]. The main reason is to avoid the visible seams. In the multi-resolution blending technique the results contains a spurious low frequency brightness change, which is not present in the original image set. It is caused by a highly varying change in brightness among the different exposures. This vast difference in the exposure settings gives rise to a lot of visible seams in the images, and also causes a lot of blur in the images. Constructing a Laplacian pyramid of higher order partially solves this problem.

III. THE NON-SUB-SAMPLED CONTOURLET TRANSFORM

The non-sub-sampled Contourlet transform is built upon non-sub-sampled pyramids and the non-sub-sampled directional filter banks and provides a shift invariant directional multi-resolution image representation. The NSCT extracts the geometric information of images, which can be used to distinguish noises from weak edges. The Non-Sub-Sampled Contourlet transform can be represented as a shift invariant version of the Contourlet transform. The NSCT is built upon iterated non-sub-sampled filter banks to obtain a shift-invariant directional multi-resolution image representation.

The Contourlet transform employs Laplacian pyramids for multi-scale decomposition, and the directional filter banks (DFB) for directional decomposition. To achieve the shift-invariance, the Non-Sub-Sampled Contourlet transform is built upon non-sub-sampled pyramids and the non-sub-sampled DFB [3].

IV. NON-SUB-SAMPLED PYRAMIDS

The building block of the non-sub-sampled pyramid is a two channel non-sub-sampled filter bank as shown in Fig.2 [3]. A non-sub-sampled filter bank has no down sampling or up-sampling operation and hence it is shift-invariant.

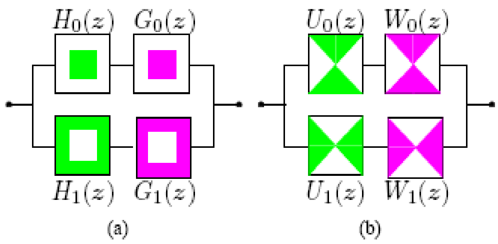

Fig 2 [3] Ideal frequency response of the building block (a) non-sub-sampled pyramid; (b) non-sub-sampled DFB

The perfect reconstruction condition is given as

$$H_0(z)G_0(z) + H_1(z)G_1(z) = 1 \qquad (1)$$

This condition is satisfied much easily than the perfect reconstruction condition for the critically sampled filter banks, and thus allows better filters to be designed.

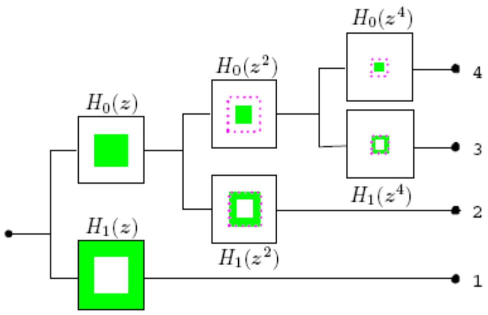

Fig.2 [3] Iteration of two-channel non-sub-sampled filter banks in the analysis part of a non-sub-sampled pyramid. For up-sampled filters, only effective pass-bands within dotted boxes are shown.

V. DIRECTIONAL FILTER BANK

The non-sub-sampled DFB is a shift-invariant version of the critically sampled DFB in the Contourlet transform. The building block of a non-sub-sampled DFB is also a two-channel non-sub-sampled filter bank. However, the ideal frequency response for a non-sub-sampled DFB is different, as shown in Fig. 3. To obtain finer directional decomposition, we iterate the non-sub-sampled DFB's. For the next level, we up-sample all filters by a quincunx matrix given by

$$Q = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \qquad (2)$$

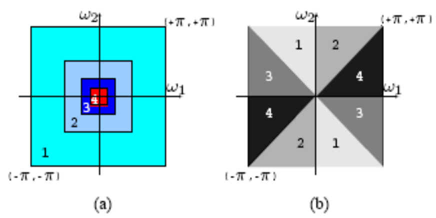

Fig. 3[3] Frequency divisions of: (a) Non-sub-sampled pyramid (b) Non-sub-sampled DFB

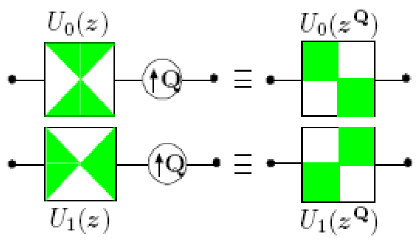

Fig.4 [3] Up-sampling filters by a quincunx matrix Q

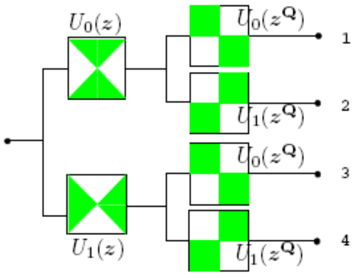

Fig.5 [3] Cascading of the Analysis Part

The frequency responses of two up-sampled filters are given in Fig. 4 and the cascading of the analysis part is shown in Fig. 5. Then we obtain a four-direction frequency division as shown in Fig. 3.

VI. NON-SUB-SAMPLED CONTOURLET TRANSFORM

The non-sub-sampled Contourlet transform combines non-sub-sampled pyramids and non-sub-sampled DFB's as shown in Fig.6. Non-sub-sampled pyramids provide multi-scale decomposition and non- sub-sampled DFB's provide directional decomposition. This scheme can be iterated repeatedly on the low-pass sub-band outputs of non-sub-sampled pyramids.

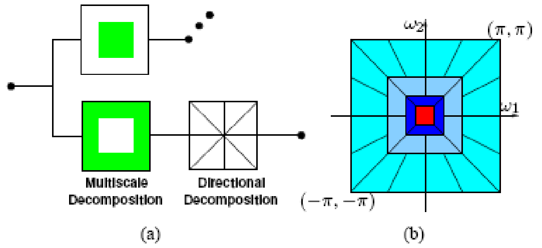

Fig. 6 [3]. The non-sub-sampled Contourlet transform

(a) Block diagram. First, a non-sub-sampled pyramid split the input into a low pass sub-band and a high-pass sub-band. Then a non-sub-sampled DFB decomposes the high-pass sub-band into several directional sub-bands. The scheme is iterated repeatedly on the low-pass sub-band.
(b) Resulting frequency division, where the number of directions is increased with frequency.

VII. PROPOSED APPROACH

7.1 The Motivation

The observation as in [2] states that the "Weak edges and fine textures are the first casualty whenever an under-exposure or an over-exposure takes place". So the proposed transform based approach should be empowered enough to detect the weak edges and textures, and to retain and enhance the same.

If the intensity distribution of the object being imaged is time-varying, then a time sequence of images of that object will also display a time-varying intensity as is the case with the multi-exposure images, and hence the image intensity is non-stationary.

This motivates us for the use of transforms such as the Haar Analysis, Wavelets, Contourlet and NSCT, instead of the usual Fourier analysis.
The basic drawbacks of fusion in the spatial domain include the following:

1. There are vast-brightness changes around the edges.
2. When we subtract the low-pass filtered version we retain the edges in the image as in the case of the laplacian Pyramid.
3. In turn we retain the Pixels that depict or get affected by a higher rate of change in the illumination.
4. Sub-Sampling these edges, gives reduced pixels.
5. That is, by sub-sampling we give more room for approximating the vacant areas with edge-pixels that themselves are greatly varying in their brightness.
6. So if the brightness change is very high the pixels that are retained will vary very high in their brightness levels, as all of these would be the edge pixels of the corresponding multi-exposure images.
7. The individual weight-maps would also vary greatly due to the vast differences in the brightness component.
8. This degrades the contrast and introduces low-frequency brightness change in the non-edge area pixels, as these are in turn are approximated from the edge-pixels.

Compared with the wavelet and other transforms, the Contourlet transform has the characteristics of multi-scale, time-frequency localization and multi-directions. However, due to the lack of translation invariance of the Contourlet transform, we use the non-sub-sampled Contourlet transform.

The other reasons for selecting the Non-Sub sampled Contourlet transform are:

In the frequency domain, both weak edges and noises lead to low-value coefficients. The non-sub-sampled contourlet transform provides not only multi-resolution analysis, but also geometric and directional representation.

The NSCT coefficients provide markers for the classification of the pixels as in [3], as Strong edge pixels, Weak edge pixels and noise.

- The strong edges correspond to those pixels with big-value coefficients in all sub-bands
- Second, the weak edges correspond to those pixels with big-value coefficients in some directional sub-bands but small-value coefficients in other directional sub-bands within the same scale.
- Finally, the noises correspond to those pixels with small-value coefficients in all sub-bands.

We have to define our threshold here; which is again a design issue. To this end, we have to modify the NSCT coefficients according to the category of each pixel by nonlinear mapping function.

The contribution of this work includes the following

The use of Non-sub-sampled filters, instead of the Laplacian filters which are sub-sampled. This improves the fusion for the images that have a greatly varying level of brightness in the exposure sequence. Overall contrast in the image improves. As regards the comparison with the Fourier domain, directional information though present is a global operator in the Fourier domain and does not have spatial info. This prevents us from distinguishing between weak edges and spurious noise. In the NSCT domain, we have a directional filter. Since in Fourier domain both the spurious frequencies and the weak edges yield small value coefficients, there is no demarcation between them. Fourier Transform gives directional components but it is a global operator and may not have spatial info.

Moreover the overall implementation is simple, as compared to the Wavelet domain. Since we use MRA in the wavelet domain we need a down and up sampling operation before compositing the sub-bands.

The work in NSCT domain believes in the conjecture that the NSCT coefficients are Gaussian Distributed, which would enable us to model them based on just their mean and the Standard Deviation. This fact also helps us in avoiding the halos and other blocking-artifacts arising out of Sharp transitions in the domain based exposure-fusion.

Gaussian distribution implies that we can model the given set of points using their mean and the standard deviation and when this is done to obtain the weight map we can use the mean and the standard deviation of these points. The NSCT exploits the fact that '"Weak edges and textures are the first casualty when an over or under exposure takes place" [2], and NSCT helps in preserving the same to a great extent due to its Directional filter bank structure.

The weights for the individual sub-band coefficients are computed as follows

1. Compute the mean and the standard-deviation for the sub-bands at that particular level.
2. Classify the pixels as
   a. Strong Edge Pixels if $\mu >= Scale*\sigma$
   b. Weak-edge and weak-texture pixels if $\mu < Scale*\sigma$ And $max >= Scale*\sigma$
   c. Noisy Pixels if $\mu < Scale*\sigma$ And $max < Scale*\sigma$
3. The Weak-edge and textured pixels are weighted by the weighting function

Given by the following expression:

$$(1/(\sigma*\sqrt{2\prod}))*\exp((X(i,j)-\mu)^2/(2*\sigma^2)) \qquad (3)$$

Where X (i, j) is the pixel value.

7.2 Implementation

The implementation for our scheme is carried out in the following steps: -

1. The input images are first decomposed using the RGB2Lab conversion.
2. The NSCT is applied only to the 'L-Channel', as it is the channel that gets affected by the brightness variations. (We use the pyramidal filter as 'maxflat' and the directional filter as 'dmaxflat7').
3. The Noise Standard Deviation of the input image is obtained as in by the formulae (Median of the highest Sub-band)/ 0.6745.
4. The coefficients obtained are classified into 3 classes as in [3] as follows: -
   a. Strong edge pixels: If mean value of the corresponding pixels of the directional sub-band coefficients at that particular level is greater than the scaled value of the Noise Standard Deviation.
   b. Weak edge pixels: If mean value of the corresponding pixels of the directional sub-band coefficients at that particular level is less than the scaled value of the Noise Standard Deviation and the maximum value of the corresponding pixels of the directional sub-band coefficients at that particular level is greater than the scaled value of the Noise Standard Deviation.
   c. Noisy Pixels: If the mean value of the corresponding pixels of the directional sub-band coefficients at that particular level is less than the scaled value of the Noise Standard Deviation and the maximum value of the corresponding pixels of the directional sub-band coefficients at that particular level is less than the scaled value of the Noise Standard Deviation.

5. As stated earlier believing in the conjecture that the NSCT coefficients are 'Gaussian' distributed, the weak edge pixels are scaled by an appropriate weighting function which is designed as follows.
   a. The mean and the Standard Deviation of the directional sub-bands for a particular level are calculated.
   b. The weighting function is defined empirically as a 'Normalized' Gaussian with the above values of the mean and the standard deviation.
6. The Noise pixels are tagged to the minimum amongst the coefficient values.

VIII. RESULTS

Consider the set of four multi-exposure house images as shown in the Fig. 1.

Fig [7]: NSCT Fused Result

Fig. [8] Set of nine multi-exposure images of the Chameleon (Images Courtesy: Erik Reinhard University of Bristol).

Fig. [9] The NSCT Fused Result of the Chameleon Image

Observations:

Fig. [2] Shows the NSCT fused result for the House Image. For the house image we get slightly under-exposed regions in the inner side of the Shelf, whereas the outside the window results are good. The house inside is still quite dark. Fig. 9 shows the NSCT fused result of the Chameleon Image. The NSCT based exposure fusion helps in preserving the contrast in the image to great extent. We are able to depict both the underexposed regions and the overexposed regions in the chameleon image to good extent. Some leaves in the chameleon image are still saturated or overexposed else it is fine.

IX. CONCLUSION

From our experiments we conclude that, the NSCT based exposure fusion can act as a good alternative for the exposure fusion in the spatial domain. The main advantage is that it gives a good contrast and avoids spurious low-frequency change in brightness. The implementation is simple and it uses the NSCT tool box available in Matlab. Thus we have proposed a novel approach to fusion in the NSCT domain for multiple-exposure images, which is an attempt to study and review the exposure-fusion in the transform domain.

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