

DCT BASED FUSION OF VARIABLE EXPOSURE IMAGES FOR HDRI

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ABSTRACT

Combining images with different exposure settings are of prime importance in the field of computational photography. Both transform domain approach and filtering based approaches are possible for fusing multiple exposure images, to obtain the well-exposed image. We propose a Discrete Cosine Transform (DCT-based) approach for fusing multiple exposure images. The input image stack is processed in the transform domain by an averaging operation and the inverse transform is performed on the averaged image obtained to generate the fusion of multiple exposure image. The experimental observation leads us to the conjecture that the obtained DCT coefficients are indicators of parameters to measure well-exposedness, contrast and saturation as specified in the traditional exposure fusion based approach and the averaging performed indicates equal weights assigned to the DCT coefficients in this non-parametric and non pyramidal approach to fuse the multiple exposure stack.

KEYWORDS

Discrete · Exposure · Cosine · Fusion · Coefficients · Transform · Contrast · Saturation · Weights

1. INTRODUCTION

The classical approach [13] to fuse multiple-exposure image set involves Laplacian pyramid and finding the characteristic parameters like Saturation, Contrast and Well-exposedness and fusing them using the Gaussian weighting scheme. Later approaches like fusing multiple exposure images with like the ones listed in [2], and transform domain approaches [reference] started to evolve. Pixel based representation of images are possible on paper and traditional display devices. For colour image displays we assign three channels R,G and B channel and assign 8 bit per pixel for each channel. So for every colour channel 256 possible values are formed. Figure 1 depicts the variable exposure stack of the Office images. Figure 2 depicts the generated HDR image. Figure 3 shows the tone-mapped LDR image.

Various HDR formats such as the ones stated below are listed in [39]

1. OPENEXR FORMAT (or EXtended Range format or '.exr' format.).

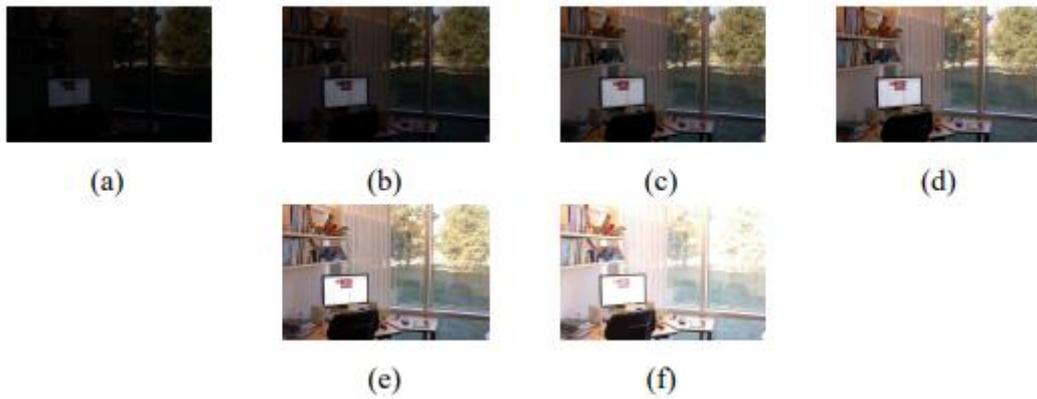


Fig. 1. Set of Six Multiple Exposure Office Images.



Fig. 2. HDR image of Office



Fig. 3. Tone-mapped image of HDR image of Office

2. Other encodings viz. scRGB48, ScRGB-nl, ScYCC-nl
3. TIFF float and the LOGLUV format.
4. HDR format (.hdr, .pic format), originally known as the Radiance picture format and Lossy HDR encodings.

In this work we perform fusion of the transform domain coefficients using a fusion rule. The multiple exposure stack is first transformed into the DCT domain and then an averaging operation is performed of the transform coefficients. This averaged output is then inverse transformed to obtain the fused output. The block variance is allowed to have a statistical distribution, and the DCT coefficients follow a Laplacian nature.[40] this then implies that we exploit the Laplacian nature of the coefficients which follows similar nature of the Laplacian distribution or Laplacian pyramidal decomposition in the spatial domain on which we perform in traditional exposure fusion.

2. CHALLENGES INVOLVED IN HDR IMAGE CAPTURE

Traditional cameras are unable to measure the radiance distribution of the scene and so it becomes unable to capture the full spectral content and dynamic range of the scene. There are inherent limitations in most digital image sensors so as to not make it possible to capture the entire dynamic range of a scene in a single exposure setting. A standard camera records multiple exposures with the right software. Selection of the right pixel to be combined to obtain the fused image is another challenging task.

Inherent assumptions include

1. Capturing device is perfectly linear
2. Each pixel in every exposure needs to be brought into the same irradiance domain
3. Corresponding pixels are averaged across the exposures.
4. Over and under exposed pixels must be excluded

Under practical considerations

1. "Cameras" are not perfectly linear.
2. Registration of various objects in the scene due to camera shake.
3. Moving objects and objects thus the following needs to be considered.
4. Understanding the nature and plotting of the Camera Response CurveFunction (CRF)
5. Involving the computations of the irradiance values.
6. Image registration techniques.
7. Ghost and Lens flare removal.

The further section discusses in detail the classical HDR imaging technique, by Debevec et. al. [2]. Then we describe the classical exposure fusion technique in the spatial domain involving pyramidal decomposition and Gaussian weighting by Mertens et. al. [1] further ahead evolving to the transform domain approaches and to the current work based on a non-pyramidal and uniform weighting approach based on DCT.

3. CRF BASED HDRI

The photochemical and the electronic reciprocity of the imaging system is exploited by the algorithm. The Hurter-Driffield characteristic curve summarizes the response of the film to variations in exposure. The curve gives a plot of the optical density D of the processed film versus the logarithm of its exposure setting. Exposure setting is obtained as the product of the irradiance E and exposure-value or exposure-time. We obtain a quantity Z which is function of the exposure setting X of a particular pixel. Consider a function f which is a conglomeration of characteristic function of the film and the non-linearities introduced by other processing steps. Initially we should recover this function f , once we have f we can recover exposure at each pixel as

$$f^{-1}(Z) \quad (1)$$

The function f is a monotonically increasing function so $f^{-1}(Z)$ is definable. If we know the exposure time $\delta(t)$, the irradiance I is obtained as

$$I = Z/(\delta(t)) \quad (2)$$

The irradiance I is proportional to the radiance L of the scene. So consider a set of exposure times $\delta(t_j)$ for a static scene with constant lighting the film reciprocity equation can be written as

$$Z_{ij} = f(I_i * \delta(t_j)) \quad (3)$$

Assuming monotonicity of f we find that f is an invertible function so we can write equation (previous) as

$$f^{-1}(Z_{ij}) = I_i * \delta(t_j) \quad (4)$$

Taking natural logarithms on both the sides we get

$$\ln(f^{-1}(Z_{ij})) = \ln(I_i) + \ln(\delta(t_j)) \quad (5)$$

Considering $h=f^{-1}(Z)$ we obtain the final equation for the characteristic curve as follows

$$h(Z_{ij}) = \ln(I_i) + \ln(\delta(t_j)) \quad (6)$$

The curve representing h is called as characteristic curve which is generalized and is independent of the input image set. Minimum two photographs with varying exposure settings are required to calculate the characteristic curve. Finally the irradiance is obtained as

$$\ln(I_i) = \frac{(\sum_{n=1}^P w(Z_{ij}) * (h(Z_{ij}) - \ln(\delta(t_j))))}{(\sum_{n=1}^P w(Z_{ij}))} \quad (7)$$

Thus we observe that the CRF based HDRI is computationally intensive and depends on log manipulations.

4. MERTEN'S CLASSICAL EXPOSURE FUSION APPROACH IN HDR

A camera of limited dynamic range is able to capture an output referred image rather than a scene referred image which is possible through HDR. This approach works basically in the spatial domain. Multiple exposure image set is obtained and each image gets treated by the estimated inverse camera response function (CRF). Weighted pixel blending is carried out to obtain the exposure fused image [1]. Sometimes a Multi Resolution Analysis (MRA) based blending is carried out which being a pyramidal decomposition approach gives rise to visible seams and blur. There also arises a need to go for higher order pyramidal decomposition.

5. COMPARISON BETWEEN HDR AND LDR ENCODINGS

A scene referred to an output transformation is a one-way irreversible transformation. This transformation is called by a process called as tone mapping. A typical tone mapping operation is a transformation in which the scene referred pixel is transformed into an output referred pixel. In the HDR image encoding scene referred N_{ss} is given more prominence than an output referred N_{ss} . Scene referred HDR encoding can be always converted to an output referred format but vice-versa is not true. So it's a one-way transformation.

6. HDR IMAGERY APPLICATIONS

The following are a list of HDR Imagery applications

1. Physically based rendering (Global Illumination)
2. Remote sensing:
3. Digital Photography:
4. Image Editing:
5. Digital Cinema (and Video):
6. Virtual Reality (VR):
7. Movie film stock.

7. RELATED WORK

Debevec et. al. [8] developed a technique in which different exposure images are combined into a single radiance map such that the pixel values are in proportion to the radiance values. Bogoni and Hansen [24] stated an in which the Luma and the Chroma components were decomposed into Laplacian pyramid and Gaussian pyramid respectively. A fusion based on Illumination estimation was suggested by [25], Vonikakis et. al. The problem of motion blur in longer exposure images was addressed by Tico et. al. [26]. In the method developed by Jinho and Okuda [27] they designed weighting functions that not dependant on exposure areas. Shen [28] used Generalized random walks to arrive at an optimal solution. Li and Kang [29] suggested a weighted sum fusion approach. Independent Component Analysis (ICA) was used by Mitianoudis and Stathaki [30] to propose their fusion scheme. Fusion involving weighted averaging of the input image stack was proposed in ([5], [6],[7]). Fusion approaches based on the irradiance values, and not the intensity values of the pixels was developed in ([8], [9]). Transform based approach are discussed in ([38], [4]). Goshtas by developed a block based fusion approach [10]. Compositing without Matte was developed in [12] and the classical exposure fusion approach in [13] are two other important techniques of compositing. Bi lateral filter based method is suggested in [1]. A Bayesian approach for Matte generation is suggested in [11]. Approaches related to Markov random field [14], boundary location information [15], Poisson Solver based [16] and an optimization approach in [17] are other fully developed techniques. Making use of the fore(background) statistics an approach was developed in [18], using motion cues in [19] and through defocus cue in [20]. A generalistic α blending approach is stated in 21].

8. SOME POPULAR HDR IMAGING TECHNIQUES USED FOR COMPARISON IN THIS WORK

We now give a brief account of some state of the art HDR imaging techniques which are popular and can be used for comparison with this technique. Ashikmin et. al.[31]

developed a technique which approach which maps the HDR image input to the luminance values possible to displayed by the display device, Banterlee et. al. [32] presented a luminance zone based approach where every zone is processed by a Tone Mapping Operator (TMO) compatible for each zone. Raman et. al. [1] developed a bilateral filter based compositing. Bruce et. al. [33] developed a fusion approach based on relative entropy. Lischinski et. al. A method based on interactive local adjustment of tonal values was proposed by [34]. Tan et. al. [35] provides a logarithmic tone mapping algorithm. Mertens et. al. [13] present a parametric classical multiple exposure fusion approach. Reinhard et. al. [36] present a traditional tone mapping methodology. In addition we have transform domain approaches [4] and edge preserving Savitsky Golay filtering based approach [37].

9. THE DISCRETE COSINE TRANSFORM (DCT)

The Discrete Cosine Transform used mainly in JPEG compression is a block transform. The basic formulation of the DCT was done by Ahmed et al. [46]. DCT exhibits unitary property and is similar to the Karhunen-Loève Transform (KLT). It has got good energy compaction efficiency and rate distortion function. In the KLT [47] we observe decorrelated transform coefficients and the signal energy is compacted in the first fewest sub-bands. The $N \times N$ cosine transform matrix $V = v(k, n)$, also known as the Discrete Cosine Transform (DCT) which is defined as follows for $k = 0$ and $0 \leq n \leq (N - 1)$

$$v(k, n) = \frac{1}{\sqrt{N}} \quad (8)$$

and for $0 \leq k \leq (N - 1)$, $0 \leq n \leq (N - 1)$

$$v(k, n) = \frac{\sqrt{2}}{\sqrt{N}} * \cos \frac{\pi(2n+1)k}{2N} \quad (9)$$

The properties of DCT are

1. DCT is not the real part of the unitary Discrete Fourier Transform (DFT)
2. DCT is real orthogonal
3. DCT is a fast transform.
4. Excellent energy compaction efficiency is seen in the DCT for highly correlated data.
5. The basis vectors of DCT are eigenvectors of the symmetric tridiagonal matrix.
6. DCT is very close to the KLT.

10. REGARDING DISTRIBUTION OF 2-D BLOCK DCT COEFFICIENTS

Pratt (1978) [41] carried out the earlier work on DCT Coefficients, it was conjectured that the DC coefficients are Rayleigh distributed assuming no level shift and the AC coefficients are Gaussian distributed according to the central limit theorem considering each pixel to be statistically independent from another. Tescher (1979) [42] and Murakami, Hatori and Yamamoto (1982) [43] indicated that the AC coefficients are Laplacian distributed, and the DC coefficients are Gaussian distributed. Reininger and Gibson [44] also asserted that DC coefficient follows a Gaussian PDF, and AC coefficients follow a Laplacian PDF. Reininger and Gibson performed the Kolmogorov-Smirnov (KS) test [45] on a 256x256 8-bit PCM grayscale images over multiple modes, and determined the best fit for the different PMFs. Observing the results of the (KS) tests [44] it is concluded that the AC block DCT coefficients follow a Laplacian distribution.

11. MOTIVATION

The drawbacks of fusion in the spatial domain include

1. Brightness changes are vast around the edges.
2. Low pass filtered version is subtracted from the original to get the Laplacian pyramid based decomposition.
3. Pixels with higher frequency that is higher rate of change of illumination are retained.
4. We get reduced number pixels by sub-sampling the edges.

5. Sub-sampling gives disadvantage of approximating the non-edge pixels with the highly varying brightness edge pixels.
6. The weight maps also depict severe variations.
7. There is degradation in the contrast and there are low frequency brightness change in the pixels which are not edge pixels.

Few of the initial steps which are performed to get a low pass filtered version and subtracting it to get the Laplacian decomposition are achieved by the one step DCT transform itself. The finding of the pixel coefficients for compositing the images is simplified due to uniform weights being assigned to each pixel and the averaging operation. We achieve a seamless blending and the results are comparable with standard exposure fusion based approach and NSST based approach.

12. OUR METHOD

The steps involved in our algorithm are as follows

1. Perform the DCT transform of all the images in the image stack.
2. The DCT Coefficients of all these images are averaged out to obtain the resultant final image in the transform domain.
3. The inverse DCT transform of the resultant image in the transform domain is performed to obtain the fused result.

Thus we can note that all the pixels have equal prominence so equal weights are assigned to all the pixels which are captured in the transform domain. The transform coefficients are empowered enough to give prominence in their luma value and chroma values according to the exposure settings.

13. RESULTS AND DISCUSSION

The DCT-based exposure fusion outputs are compared with the techniques described in ([1],[4],[13],[31],[32],[33],[34],[35],[36] and [37]). The PSNR and the SSIM scores are improved. There is a decrease in error i.e. the IMMSE scores. High Q Scores are obtained using the VDP metric [23]. For the following set of images, shown in figures 5, 7, 9, 11 kindly refer to the table 1 shown below for knowing which of the sub-figure was generated using what approach.

Table 1. List of the sub figures indexes, showing results for images generated using various approaches used for comparison in this work.

Sub figure index	Results using method described in
a	S G Filter based [37]
b	Ashikmin et. al. [31]
c	Banterlee et. al. [32]
d	Shanmuga et. al. [1]
e	Bruce et. al. [33]
f	Lischinski et. al. [34]
g	Logarithmic et. al. [35]
h	Mertens et. al. [13]
i	Reinhard et. al. [36]
j	NSST Based [4]
k	Our Method in this paper

The PSNR, SSIM, IMMSE scores and the Q factor score [23] are tabulated in the table 2.



Fig. 4. Variable Exposure House Images.

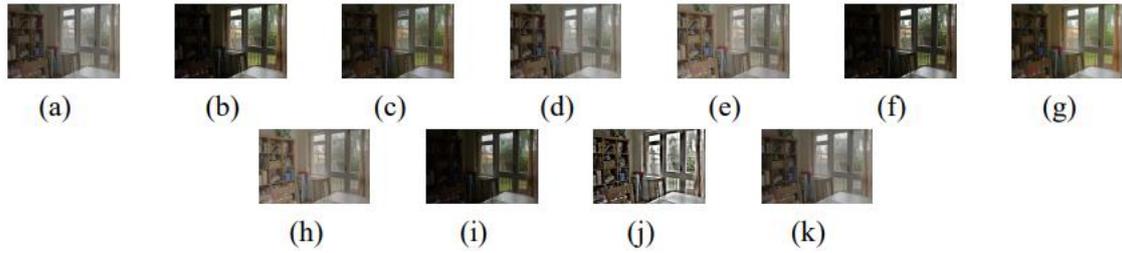


Fig. 5. Results generated for House images with approaches mentioned in table 1.



Fig. 6. Variable exposure Window Images.

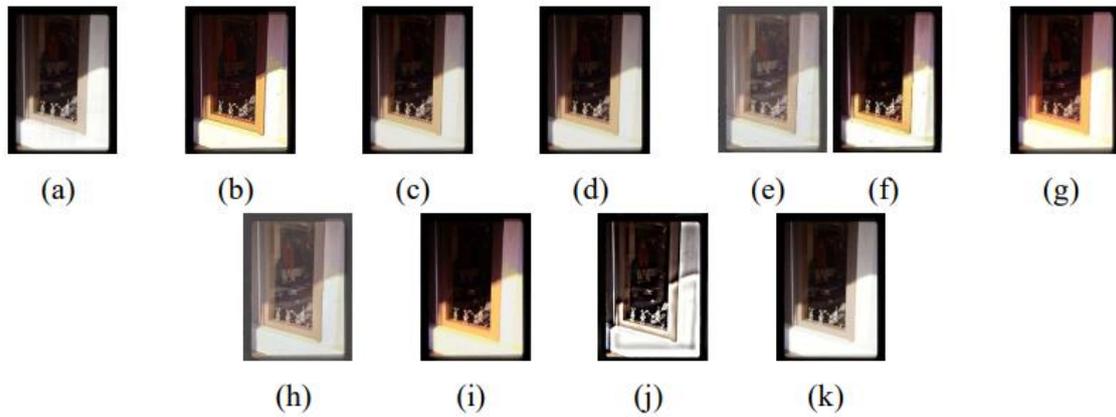


Figure 7. Results generated for Windows images with approaches mentioned in table 1.



Figure 8. Variable exposure Door Image set.



Figure 9. Results generated for Door images with approaches mentioned in table 1.



Figure 10. Variable Exposure Garage Image set.

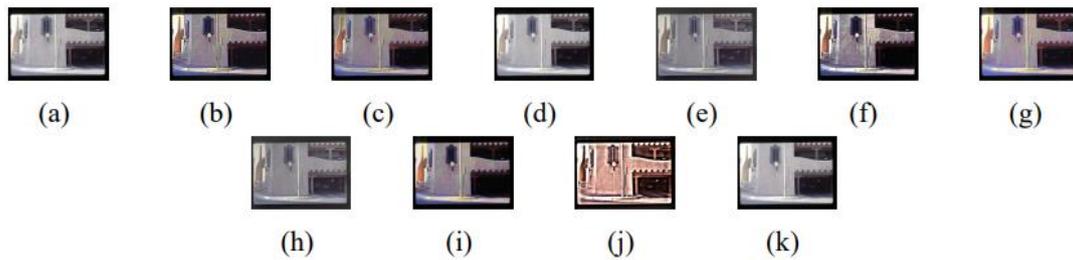


Figure 11. Results generated for Garage images with approaches mentioned in table 1

Table 2. Performance parameters for the DCT-based Exposure Fusion and other state of the art approaches described in ([1],[4],[13],[31],[32],[33],[34],[35],[36]and[37])

Image	Method	PSNR	IMMSE	SSIM	Q
HOUSE IMAGE	Ashikmin[31]	66.1274	0.0300	0.9877	98.0525
	Banterlle[32]	70.1584	0.0179	0.9890	98.1235
	BFbased[1]	67.0624	0.0261	0.9878	98.2014
	Bruce[33]	62.8707	0.0523	0.9839	98.1466
	Lischinski[34]	64.7319	0.0375	0.9865	98.0537
	Logarithmic[35]	68.5648	0.0214	0.9885	98.1503
	Mertens[13]	62.8707	0.0523	0.9839	98.466
	Reinhard[36]	63.5942	0.0366	0.9869	98.1023
	SGFilterBased[37]	68.1417	0.0226	0.9883	98.1874
	NSSTBased[4]	63.6711	0.0452	0.9866	98.0366
DCTBased(OurMethod)	67.7379	0.0238	0.9881	98.1997	
DOOR IMAGE	Ashikmin[31]	61.7326	0.0649	0.9838	98.0960
	Banterlle[32]	61.5589	0.0672	0.9834	98.1026
	BFbased[1]	70.6514	0.0170	0.9892	98.2521
	Bruce[33]	61.1196	0.0733	0.9892	98.1909
	Lischinski[34]	58.2465	0.1326	0.9748	98.0905
	Logarithmic[35]	62.2420	0.0589	0.9842	98.169
	Mertens[13]	61.1196	0.0733	0.9822	98.1909
	Reinhard[36]	58.0458	0.1384	0.9737	98.1865
	SGFilterBased[37]	70.89	0.0167	0.9893	98.2389
	NSSTBased[4]	63.8374	0.0438	0.9864	98.1472
DCTBased(OurMethod)	71.0176	0.0165	0.9893	98.2925	
WINDOW IMAGE	Ashikmin[31]	65.4498	0.0333	0.9875	98.0258
	Banterlle[32]	65.4498	0.0333	0.9875	98.0258
	BFbased[1]	67.2379	0.0255	0.9882	98.0855
	Bruce[33]	61.0632	0.0745	0.9810	98.0566
	Lischinski[34]	65.4698	0.0332	0.9875	98.0036
	Logarithmic[35]	66.7944	0.0271	0.9881	98.0285
	Mertens[13]	61.0368	0.0745	0.9810	98.0566
	Reinhard[36]	66.8427	0.0719	0.9881	98.0362
	SGFilterBased[37]	70.6617	0.0170	0.9892	98.1223
	NSSTBased[4]	66.9991	0.0263	0.9883	98.1374
DCTBased(OurMethod)	71.7756	0.0154	0.9894	98.1227	
GARAGE IMAGE	Ashikmin[31]	66.4497	0.0285	0.9880	98.0795
	Banterlle[32]	65.1389	0.0351	0.9871	98.0327
	BFbased[1]	70.0185	0.0182	0.9890	98.2360
	Bruce[33]	63.7948	0.0442	0.9854	98.1752
	Lischinski[34]	67.6633	0.0240	0.9884	98.0466
	Logarithmic[35]	68.7227	0.0210	0.9888	98.0713
	Mertens[13]	63.7948	0.0442	0.9854	98.1752
	Reinhard[36]	67.2374	0.0255	0.9882	98.1057
	SGFilterBased[37]	70.6275	0.0171	0.9891	98.2424
	NSSTBased[4]	63.6227	0.0455	0.9862	98.1145
DCTBased(OurMethod)	70.8156	0.0168	0.9891	98.2364	

14. CONCLUSIONS

Thus we have developed a method for performing fusion of multiple exposure images using the DCT-based transform domain approach and studied the results. The results favor the use of DCT-based multi-exposure image fusion for the High Dynamic Range Imaging problem.

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