OPTIMIZATION OF MEF-SSIM BY GRADIENT ASCENT METHOD

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Abstract: Here we propose a multi-exposure image fusion (MEF) algorithm that optimizes a novel objective quality measure, namely the color MEF structural similarity (MEF-SSIM) index. The design methodology is substantially different approach to design MEF algorithms. In particular, we directly operate in the space of all images, iteratively searching for the image that optimizes MEF -SSIM. Specifically, we first construct the MEF-SSIM index by improving upon and expanding the application scope of the existing MEF-SSIM algorithm. We then describe a gradient ascent-based algorithm, which starts from any initial point in the space of all possible images and iteratively moves towards the direction that improves MEF-SSIM until convergence. The proposed algorithm consistently produces better quality fused images both visually and in terms of MEF-SSIM. The final high quality fused image appears to have little dependence on the initial image. The proposed optimization framework is readily extensible to construct better MEF algorithms when better objective quality models for MEF are available.

***Index Terms** -Multi-exposure image fusion (MEF), gradient ascent, structural similarity (SSIM), perceptual Optimization.*

I. INTRODUCTION

One of the key bottlenecks of current sensors and displays lies in their small dynamic range[1], which cannot replicate the maximum luminance of many practical natural scenes.Several high dynamic range (HDR) imaging technologies have been developed over the past decade in order to continuously increase the dynamic range of sensors
. When the camera has a low or high exposure condition, images taken by ordinary digital cameras typically suffer from a lack of clarity in the under-exposed and over-exposed regions. High dynamic range imaging (HDR) addresses this issue by taking multiple images and combining them together at different exposure rates. This method was commonly used in digital camera and mobile devices. In general, current solutions to HDR imaging can be split into two categories: methods based on tone mapping and methods based on image fusion. Multi-exposure digital image fusion (MEF) is a cost-effective technique that bridges the gap between the high dynamic range (HDR) of natural-scene luminance rates and the low dynamic range (LDR) of normal standard display devices [1]. An MEF algorithm's input sequence consists of multiple images of the same scene taken at different levels of exposure, each of which captures partial scene detail. Most current multi-exposure fusion approaches are basically assumed that the scene is unchanged during diverse captures.When fusing images taken in complex scenes including camera action or motion artifacts, however, the above described approaches may cause serious distortions. Several forms of multi-exposure image matching have been introduced to remove the impacts of object movement [2].
In recent years, there have been many algorithms suggested, none of which were developed to optimize a promising quality measure that fits well with human visual perception.In addition, all extant algorithms begin with the predefinition of a hierarchical computational framework for MEF (e.g., multiresolution transformation and transform domain fusion followed by image reconstruction), with limited and indirect help for the validity and optimality of such a structure.Additionally, most modern MEF algorithms are illustrated using a limited number of handpicked instances
, with no arbitrary verifications on databases containing adequate differences in picture content or objective assessmen t by well-established and subject validated consistency models [3].
Unlike existing MEF methods that employ a predefined computational structure, we directly explore in the space of all images, searching for the image that optimizes MEF-SSIMc, which is a more a model built upon MEF-SSIM. More specifically, we first construct the MEF-SSIMc model by expanding the application scope of MEF-SSIM from grayscale to color images and by better accounting for the impact of luminance changes on image quality. We then derive an analytic form of the gradient of MEF-SSIMc in the space of all images and use it to iteratively search for the optimal MEF-SSIMc image.

II. LITERATURE SURVEY

Much work has been done in the assessment of image quality where number of algorithms have been used, one of these algorithms is multiexposure image fusion utilizing structural similarity index, and

some of the references are used to apply the algorithm to this study extensively. Shutao Li and Xudong Kang, [11] proposed a weighted sum based on multi-exposure image fusion method. This work which consists of two main steps: three image features composed of local variance; brightness and colour dissimilarity are first measured to evaluate the weight maps purified by recursive filtering. Then, the fused images are established by weighted sum of source images. The main advantage of the proposed method rest in a recursive filter based weight map filtered step which is able to obtain précised weight maps for image fusion. Another advantage is that a new histogram equalization and median filter based movement identification method that is proposed for fusing multi-exposure images in dynamic scenes which contain moving objects. Zhengguo Li, Jinghong Zheng, Zijian Zhu, and Shiqian Wu, [12] introduced an exposure fusion scheme for differently exposed images with motion objects. The proposed method which incorporates a ghost removal algorithm in a low dynamic range and a selectively detail enhanced exposure fusion algorithm. The proposed ghost removal algorithm includes a bidirectional normalization-based method for the identification of non-consistent pixels. Detail-enhanced exposure fusion algorithm encompasses a content adaptive bilateral filter, which extracts selective details from all the verified images simultaneously in gradient domain. Rui Shen, Irene Cheng, Jianbo Shi, and Anup Basu, [13] proposed a single captured image of a realworld scene, generally it is insufficient to disclose all the details due to under or over exposed regions. To solve this problem, images of same scene can be first captured under different exposure settings after that they are combined into a single image using image fusion techniques. K. Ma, K. Zeng, and

Z. Wang, [14] proposed Multi-exposure image fusion (MEF) which is considered as an effective quality enhancement technique. This technique is widely adopted in consumer electronics, but little work has been dedicated to the perceptual quality assessment of multi-exposure fused images. They first build an MEF database which is carried out a subjective user study to access the quality of images produced by different MEF algorithms. Shutao Li, Xudong Kang, and Jianwen Hu, [15] proposed a fast and effective image fusion for creating a highly informative fused image through merging multiple images. They proposed a method which is based on a two-scale decomposition of an image into a base layer containing large scale variations in intensity, and also a detail layer capturing small scale details. A new guided filtering- based weighted average technique is proposed to make full use of spatial consistency for image fusion and detail layers. The original MEF-SSIM will exclude the luminance comparison. When it comes to constructing MEF algorithms, the mean intensity of each color patch needs to be explicitly mentioned.

Inspired by the method we estimate the desired mean intensity of the fused image patch by

$$\bar{l} = \frac{\sum_{k=1}^{N} u(\mu_k, l_k)\, l_k}{\sum_{k=1}^{N} u(\mu_k, l_k)} \qquad (1)$$

$$S(\{x_k\}, y) = \frac{(2\tilde{\mu}_x \mu_y + C_1)(2\tilde{\sigma}_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (2)$$

The construction of MEF-SSIM follows the definition of the SSIM is by considering a large sequence of images and determining the quality measure for each of the image statistical methods can be used to determine an overall quality measure of the compression method. Defining image quality in terms of a divergence from the original situation, quality measure becomes technical in the sense that they can be objectively determined in terms of deviations from the original models. Image quality although related to the subjective perception of an image e.g., Human looking at a photograph.

III. PROPOSED METHODOLOGY

The database consists of source image a list of images which is set of images under various levels of exposure which are taken to prepare the images for multi-exposure image fusion. We are then prone to pre-processing. Such images were then merged to produce a fused image of high quality which is taken from an original image. There is not much detail in the original image that is used as feedback, and the synthesized output image is more descriptive than the input image. The data usually contains multiple images of the same scene taken at different levels of exposure. Using the Laplacian Pyramid [16], all input artifacts were compressed into several images.

Multiresolution transformations are accepted as the most useful way processing the details representing both artifacts for image fusion purposes. The discrete transformation of wavelets has become an extremely useful fusion method.For consumer electronic applications, multiexposure image fusion is preferable as it does not involve the process of HDR image construction which increases some computational costs.Many techniques for fusion of images with multiexposure were introduced.Multiresolution transformations have been recognised in recent years as a very useful way of processing the information content of images for image fusion purposes. The discrete wavelet transform has become a very useful tool for fusion. These methods show a better performance in spatial and spectral quality of the fused image. The notion of multi- resolution analysis was initiated by Burt and Adelson who introduced a multi resolution image representation called Gauss-Laplacian pyramid. Hence, multi resolution analysis has become a very useful tool for analyzing remote sensing images. Their idea is to decompose an image into a set of band pass filtered component images, each of which represent a different band of spatial frequency. Other researchers such as Mallat further extended this idea and Meyer, who established a multi resolution analysis for continuous functions in connection with wavelet transforms. The advantage of wavelet transforms over Fourier transforms is temporal resolution that is it captures both frequency and time information.

IV. RESULTS

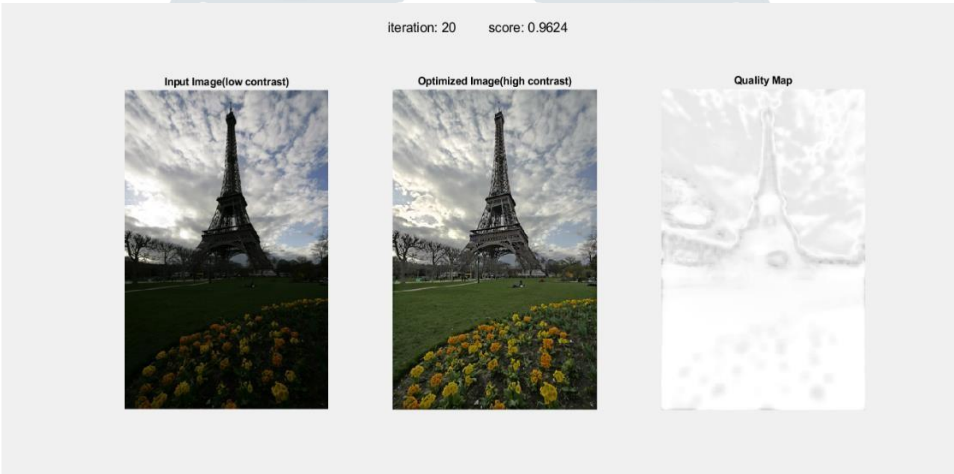

Fig1 (A): Quality map at 20 iterations.

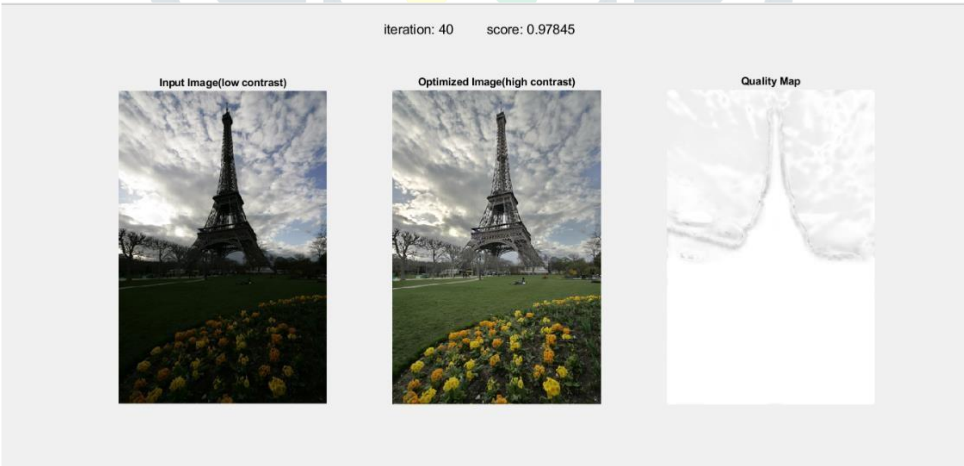

Fig 1(B): Quality map at 40 iterations

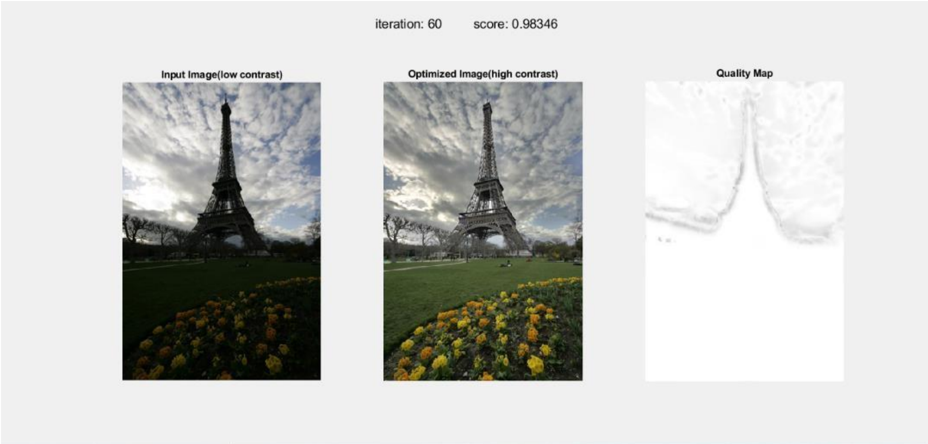

Fig1 (C): Quality map at 60 iterations.

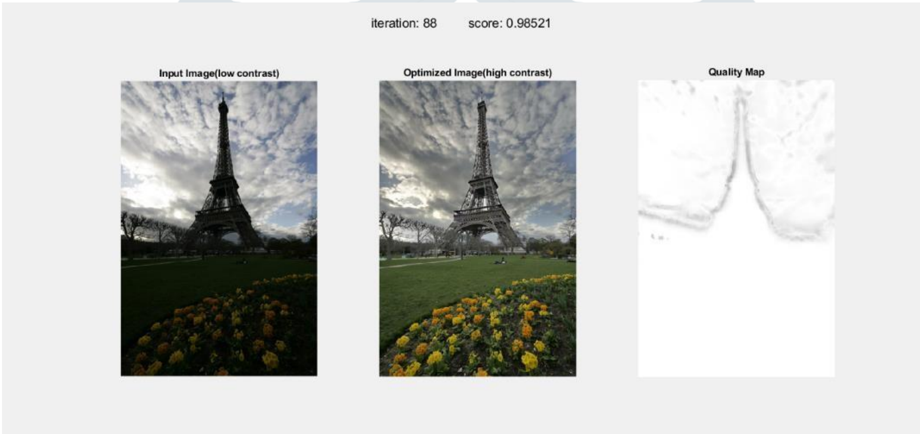

Fig 1(D): Quality map at 88 iterations.

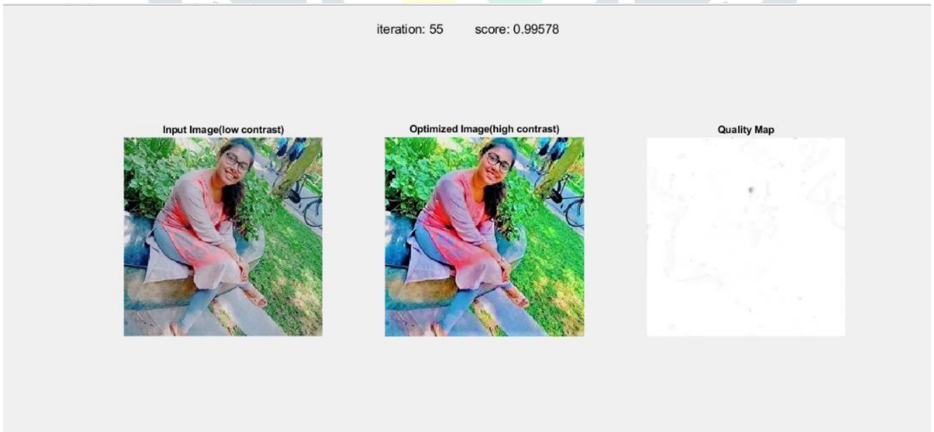

Fig 2: Quality map at 55 iterations.

4.1 Results

TABLE 4.1: MEF-SSIMC COMPARISONS OF INITIAL & OPTIMIZES IMAGES.

Image		Mertens09 [11]	Zhang12[13]	Li1 3 [10]	**Ours**
Arno	Initial	0.9474	0.9342	0.9002	0.98884
	Optimized	0.9935	0.9935	0.9934	0.98946
Balloons	Initial	0.9509	0.8478	0.9470	0.98821
	Optimized	0.9913	0.9913	0.9913	0.98983
Chinese garden	Initial	0.9577	0.8995	0.9819	0.99295
	Optimized	0.9926	0.9929	0.9926	0.99271
Church	Initial	0.9503	0.8688	0.9870	0.99010
	Optimized	0.9928	0.9905	0.9928	0.99266
Lamp	Initial	0.9451	0.9062	0.9376	0.97761
	Optimized	0.9806	0.9807	0.9805	0.97857
Landscape	Initial	0.9914	0.9618	0.9764	0.99629
	Optimized	0.9963	0.9963	0.9961	0.99814
Lighthouse	Initial	0.9706	0.9582	0.9261	0.99675
	Optimized	0.9953	0.9953	0.9950	0.99588
Madison Capitol	Initial	0.9298	0.8520	0.9280	0.95981
	Optimized	0.9802	0.9802	0.9799	0.96604
Set	Initial	0.9739	0.9524	0.9656	0.99954
	Optimized	0.9953	0.9954	0.9953	0.99860
Window	Initial	0.9381	0.8881	0.9705	0.98447
	Optimized	0.9847	0.9889	0.9861	0.98563
Average	Initial	**0.9555**	**0.9174**	**0.9530**	**0.98745**
	Optimized	**0.9892**	**0.9905**	**0.9903**	**0.98875**

TABLE 4.2: RUNTIME COMPARISONS OF INITIAL & OPTIMIZES IMAGES.

Source Images	**Initial image**	**Optimized image**
Arno	4.710945	1.947939
Balloons	4.626530	1.984384
Chinese garden	1.975782	4.641826
Church	2.012339	1.955858
Lamp	2.362269	2.380989
Landscape	2.236619	2.082543
Lighthouse	1.953330	1.957631
Madison Capitol	5.069097	2.261601
Set	1.877999	2.020806
Window	2.595770	2.183628

TABLE 4.3: GRADIENT COMPARISONS OF INITIAL & OPTIMIZES IMAGES.

Source Images	**Initial Gradient**	**Optimized Gradient**
Arno	0.16512	0.14038
Balloons	0.23959	0.15949
Chinese garden	0.58824	0.59032
Church	0.60157	0.62857
Lamp	0.61252	0.61252
Landscape	0.22891	0.51563
Lighthouse	0.07355	0.15196
Madison Capitol	0.34238	0.17850
Set	0.04142	0.19912
Window	0.25821	2.58130

V. CONCLUSION

We propose a different approach to design MEF algorithms by directly operating in the space of all images. Many MEF algorithms involve one or more free parameters in which the best values largely depend on the image content. Iteratively searching for an image that improves MEF-SSIM which is advanced MEF image quality assessment model constructed upon existing MEF-SSIM. The proposed algorithm is iterative so it is not suitable for real time applications. This algorithm can find local optima because the non-convexity of MEFSSIM is highly desirable. Image fusion has become a generally used technology to increase the visual interpretation of the images in different applications like increased vision system, medical diagnosis, robotics, military and surveillance. It has been commonly used in many fields such as object identification, classification and change detection.

REFERENCES

[1] E. Reinhard, W. Heidrich, P. Debevec, S. Pattanaik, G. Ward, and K. Myszkowski, High Dynamic Range Imaging: Acquisition, Display, and Image-Based Lighting. San Mateo, CA, USA: Morgan Kaufmann, 2010.

[2] Shutao Li, Member, IEEE and Xudong Kang, Fast Multi-exposure Image Fusion with Median Filter and Recursive Filter, IEEE Transactions on Consumer Electronics, Vol. 58, No. 2, May 2012.

[3] E. Reinhard, W. Heidrich, P. Debevec, S. Pattanaik, G. Ward, and K. Myszkowski, High Dynamic Range Imaging: Acquisition, Display, and Image-based Lighting. Burlington, MA, USA: Morgan Kaufmann, 2010.

[4] J. Im, S. Lee, and J. Paik, "Improved elastic registration for ghost artifact free high dynamic range imaging," IEEE Trans. Consumer Electronics, vol. 57, no. 2, pp. 932–935, May 2011.

[5] Z. Li, J. Zheng, and S. Rahardja, "Detail-enhanced exposure fusion," IEEE Trans. Image Process., vol. 21, no. 11, pp. 4672–4676, Nov. 2012.

[6] S. Li, X. Kang, and J. Hu, "Image fusion with guided filtering," IEEE Trans. Image Process., vol. 22, no. 7, pp. 2864–2875, Jul. 2013.

[7] Kede Ma , Student Member, IEEE, Zhengfang Duanmu , Student Member, IEEE, Hojatollah Yeganeh, Member, IEEE, and Zhou Wang, Fellow, IEEE, Multi-Exposure Image Fusion by Optimizing A Structural Similarity Index, IEEE transactions on computational imaging, vol. 4, no. 1, march 2018.

[8] Z. Liu, E. Blasch, Z. Xue, J. Zhao, R. Laganiere, and W. Wu, "Objective assessment of multiresolution image fusion algorithms for context enhancement in night vision: A comparative study," IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 1, pp. 94–109, Jan. 2012.

[9] S. Li and X. Kang, "Fast multi-exposure image fusion with median filter and recursive filter," IEEE Trans. Consum. Electron. vol. 58, no. 2, pp. 626–632, May 2012.

[10] Z. Li, J. Zheng, Z. Zhu, and S. Wu, "Selectively detail-enhanced fusion of differently exposed images with moving objects," IEEE Trans. Image Process., vol. 23, no. 10, pp. 4372–4382, Oct. 2014.

[11] R. Shen, I. Cheng, J. Shi, and A. Basu, "Generalized random walks for fusion of multi-exposure images," IEEE Trans. Image Process., vol. 20, no. 12, pp. 3634–3646, Dec. 2011.

[12] K. Ma, K. Zeng, and Z. Wang, "Perceptual quality assessment for multi exposure image fusion," IEEE Trans. Image Process., vol. 24, no. 11, pp. 3345–3356, Nov. 2015.

[13] Shutao Li, Xudong Kang, and Jianwen Hu, "Image Fusion with Guided Filtering", IEEE transactions on image processing, vol. 22, no. 7, july 2013.

[14] P. Burt and T. Adelson, "The Laplacian pyramid as a compact image code," IEEE Trans. Commun., vol. 31, no. 4, pp. 532–540, Apr. 1983.

[15] T. Mertens, J. Kautz, and F. Van Reeth, "Exposure fusion: A simple and practical alternative to high dynamic range photography," Comput. Graph. Forum, vol. 28, no. 1, pp. 161–171, 2009. (Mertens07).

[16] N. D. Bruce, "Expoblend: Information preserving exposure blending based on normalized log-domain entropy," Comput. Graph. vol. 39, pp. 12–23, Apr. 2014.

[17] R. Shen, I. Cheng, J. Shi, and A. Basu, "Generalized random walks for fusion of multi-exposure images," IEEE Trans. Image Process., vol. 20, no. 12, pp. 3634–3646, Dec. 2011.