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Image Quality Assessment Using Multi Exposure Image Fusion by Optimizing Structural Similarity Index

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--ABSTRACT---
Multi exposure image fusion structural similarity index (MEF-SSIM) is an effective quality enhancement method which is a novel objective quality measure. In this paper the image quality assessment of multi exposure fused images is improved by using MEF-SSIM algorithm. The design philosophy here is substantially different from already existing ones. First build an MEF database and carry out perceptive study to evaluate the quality of images generated by different MEF algorithms. Specifically, first construct the MEF-SSIM by optimizing upon and expand the application scope of existing MEF-SSIM algorithm. Then describe gradient ascent algorithm, this starts from initial point in the space of images and moves iteratively towards direction that improves MEF-SSIM. Instead of pre defining the systematic computational structure for MEF, directly operate on the space of all images by searching image that improves MEF-SSIM. The final high quality images have little dependency on initial image. A novel objective image quality assessment algorithm for MEF images based on structural similarity and a measure of patch consistency methods have been used. A pre defining computational structure been used like multi-resolution transformation followed by image reconstruction.
KEYWORDS - *MEF-SSIM, Gradient ascent, image quality assessment, Multi exposure image fusion (MEF).*

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I. INTRODUCTION

The image fusion is one of the important branches of data fusion. Data fusion techniques has been designed to allow integration of different information sources and also to take advantage of complementary. There is no unique definition for image fusion, Few image fusion definitions are given below: Image fusion is the combination of two or more different images to form a new image by using a certain algorithm (Genderen and Pohl 1994)[1].Image fusion is the process of combining information from two or more images of a scene into a single composite image that is more informative and is more suitable for visual perception or computer processing. (Guest editorial of Information Fusion, 2007)[2]. Image fusion is a process of combining images, obtained by sensors of different wavelengths simultaneously viewing of the same scene, to form a composite image. Multi-exposure image fusion (MEF) is considered an effective quality enhancement technique that is widely adopted in consumer electronics [3]. Images taken by ordinary digital cameras usually suffer from lack of details in the under-exposed and over-exposed areas if the camera has a low or high exposure setting, High dynamic range (HDR) imaging solves this problem by taking multiple images at different exposure levels and merging them together, This technique has been widely used in digital camera and mobile phones. Existing HDR imaging approaches can be divided into two categories: tone mapping based methods and image fusion based methods[4]. Multi exposure image fusion (MEF) is a cost effective technique that bridges the gap between the high dynamic range (HDR) of luminance levels in natural scenes and the low dynamic range (LDR) of standard display devices [5].

The input sequence of MEF algorithm consists of multiple pictures of the same scene that is an image sequence taken at different exposure levels, each image which captures partial information of the scene. Most existing multi-exposure fusion methods basic assumption is that the scene is static during different captures. While fusing images taken in dynamic scenes which contain camera movement or motion objects, the methods mentioned above may produce serious distortions[4]. To remove the impacts of camera movement, many multi exposure image alignment methods have been proposed [6]. There are many algorithms have been proposed in recent years, none of them has been designed to optimize a promise quality measure that corresponds well with human visual perception. For example, a commonly used approach is to maximize the fine details in fused images as a way to create vivid appearance [7], [8]. Moreover, all existing algorithms start by pre-defining a systematic computational structure for MEF (*e.g.*,multi-resolution transformation and transform domain fusion followed by image reconstruction), with weak and indirect support of the validity and optimality of such a structure[9]. In addition, most existing MEF algorithms are demonstrated using a limited number of hand-picked examples, without subjective verifications on databases that contain sufficient variations of image content or objective assessment by well-established and subject-validated quality models [10].

II. LITERATURE REVIEW

Much work has been done in image quality assessment where number of algorithms have been used one such among those algorithm is multi exposure image fusion using structural similarity index, some of the references are taken to refer the algorithm thoroughly to this work. 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 real-world 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.

III. METHODOLOGY

A. Multiple image sequence

The database consists of source image, for multi exposure image fusion a sequence of images that is set of images under different exposure levels which are taken to train the images. Then they are subjected to pre-processing. These images then fused to get a high quality fused image, which is taken a initial image. The source image does not contain much information which is taken as input and the synthesised output image is more informative then the input image. Generally the input has multiple pictures of same scene taken at different exposure levels. All input images were scaled into several down-sampled layers by using the Laplacian pyramid [16]. Multi-resolution transforms has been recognized as the most useful approach to analyse the information which contain all images for the purpose of image fusion. The discrete wavelet transform has become a most useful tool for fusion.

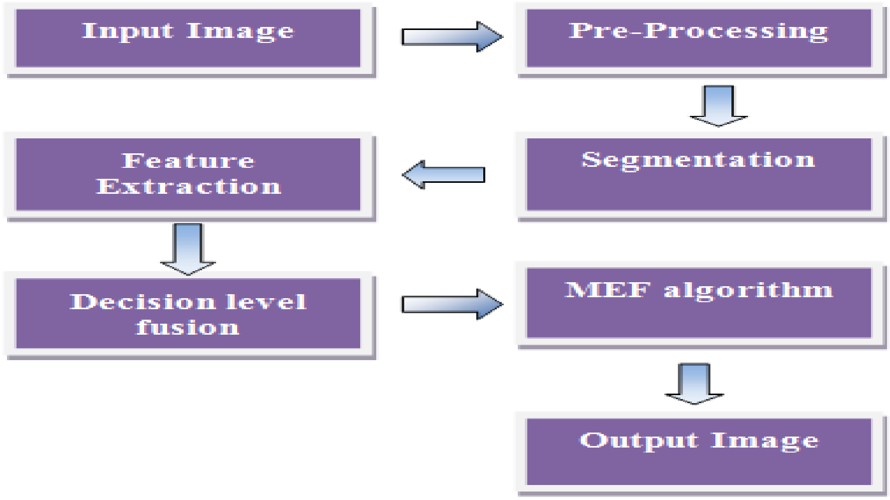

Fig1. Flowchart of the Designed system

B. MEF-SSIM

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

$$\hat{I} = \frac{\sum_{k=1}^{K} u(\mu_k, I_k) I_k}{\sum_{k=1}^{K} u(\mu_k, I_k)} \quad (1)$$

The construction of MEF-SSIM follows the definition of the SSIM is

$$S(\{x_k\}, y) = \frac{(2\mu_{\hat{x}}\mu_y + C_1)(2\sigma_{\hat{x}y} + C_2)}{(\mu_{\hat{x}}^2 + \mu_y^2 + C_1)(\sigma_{\hat{x}}^2 + \sigma_y^2 + C_2} \quad (2)$$

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.

IV. RESULTS

Twenty four source image sequence are selected in this work, which spread diverse scenes containing both light and dark regions with different color occurrences. On the other side, the proposed algorithm is initialized with the fused images. These include two simple operators they are local and global energy which linearly fuse the images, they used as weighting factors denoted by LE and GE, respectively, and sophisticated ones with different perceptual emphasis such as Mertens09 [10], Shen11 [4], Gu12 [6], Bruce14 [9], Shen14 [7], and Ma15 [8].

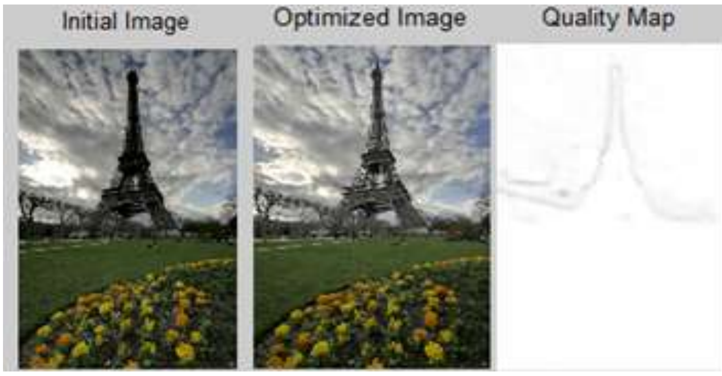

Fig2. Output Simulation results of 'Tower' for 68 iterations

The above fig.2 explains, the simulation window consists of three images: first is initial image, second is optimized image, third is quality map. The initial image indicates sequence of images in the data base is fused and forms an initial image. The source image is fused with the test image, here with sequence of source images the test image is taken from detailed enhancement algorithm based on Mertens07[3]. It can be seen that it fails to preserve some relevant details such as top of the tower and the brightest region of the cloud at the middle left part of the image. Those details are faithfully recovered in the MEF-SSIM optimized image. Initially the fused image value is 0.9541, at the 68th iteration in this simulation 0.99244 value is obtained which means the image is more bright, where brighter indicates better quality. The third part is quality map which indicates the quality improvement during MEF-SSIM optimization. Higher brightness indicates better quality.

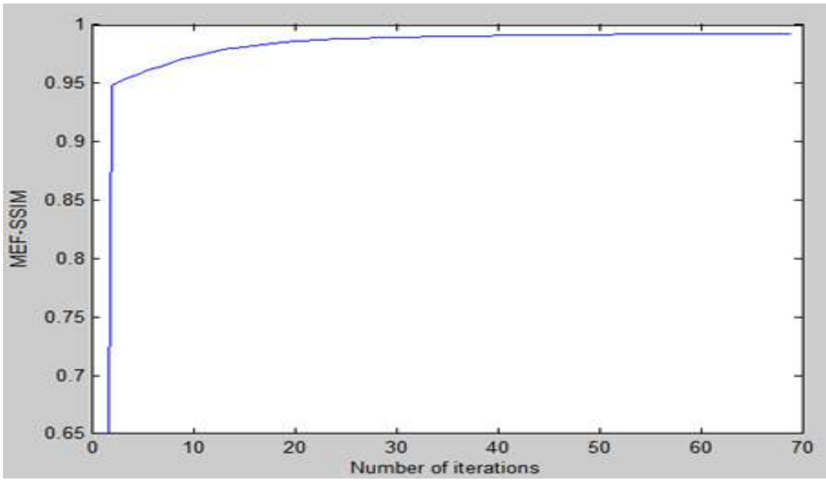

Fig3. MEF-SSIM as a function of iteration on the 'Tower' sequence with initial fused images created by MEF algorithm

The above fig 3 show value of MEF-SSIM as a function of iteration on the 'Tower' sequence using different initial images taken at different exposure levels as starting point. By observing the graph, the MEF-SSIM values increases monotonically with iterations.

Table1. Comparison Results

IMAGE	SSIM	MERTENS09 [17]	BRUCE13 [18]	SHEN11 [19]	PROPOSED METHOD
KLUKI	INITIAL	0.9323	0.9282	0.9341	0.93231
	OPTIMIZED	0.9852	0.9854	0.9852	0.9852
TOWER	INITIAL	0.9541	0.9223	0.9201	0.9541
	OPTIMIZED	0.9925	0.9925	0.9925	0.9924
BALLOONS	INITIAL	0.9509	0.6044	0.9343	0.9074
	OPTIMIZED	0.9913	0.9911	0.9913	0.9935
OFFICE	INITIAL	0.9627	0.9224	0.9439	0.9626
	OPTIMIZED	0.9906	0.9915	0.9898	0.9906
HOUSE	INITIAL	0.9196	0.8377	0.8867	0.9195
	OPTIMIZED	0.9690	0.9692	0.9691	0.9690

ARNO	INITIAL	0.9474	0.9258	0.9604	0.9359
	OPTIMIZED	0.9935	0.9935	0.9936	0.9934
FARMHOUSE	INITIAL	0.9760	0.8618	0.9450	0.9728
	OPTIMIZED	0.9331	0.9929	0.9930	0.9930
LIGHTHOUSE	INITIAL	0.9706	0.9571	0.9472	0.9671
	OPTIMIZED	0.9953	0.9953	0.9953	0.9953

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 MEF-SSIM 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.

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