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An Advanced Multi-Exposure Image Fusion Technique to Enhance The QoS for HDR Images

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ABSTRACT

Image fusion is carried out on images taken at different exposures levels to get well exposed image that contains details related to the entire dynamic range (DR). Unwanted objects can emerge or disappear from the image while capturing the image at different exposure levels, thus results in ghost artifacts in the fused image. Removal of such ghosting artifacts at less computational cost to produce high dynamic range image (HDRI) is of significant consideration. In this work, data base is made which contains source input images having various presentation levels (≥ 3) along with combined pictures created by both traditional and best in class image fusion algorithms, then we have suggested an advanced multi exposure image fusion (AMEF) technique to improve the QoS for HDR Images. The main objective of the study is to produce the ghost-free HDR image from multiple images taken at different exposure levels. A moving object removal method (MORM) is used to remove the ghosting relics in the fused image. Finally, we need to compare the achieved results of the proposed technique with the existing techniques, the software considered for the implementation is MATLAB.

Key words: Image enhancement, ghost removal, HDR imaging, MEF.

1. INTRODUCTION

Current image capturing devices failed to capture whole information in a picture through a one-time exposure. There is a difference of dynamic range that results while capturing the scene from the imaging device and the one observed from the human eyes. It critically impacts image visuals in addition to key information maintenance [1, 2]. Usually, human eyes possess an extensive dynamic range compares to current imaging device. On behalf of colour as well as brightness, picture taken through the imaging device is dissimilar from the individual noticed by human eyes in an actual scene like an image that capture during night time. Consequently, High dynamic range (HDR) imaging methods are presented to work out the aforementioned disparity concerns. As a category of HDR methods, multi exposure image fusion (MEF) related methods be able to take out the complete image data from various exposure images and fuse into a single image. MEF bypasses the intermediate HDR image construction step and directly yields an low dynamic range (LDR) image that can be displayed on standard viewing devices. MEF has considered extensive consideration as the earliest journal in 1980 [3].

MEF is a method which is efficient and prefers a series of input images through MEs and creates a one fused image with more quality specifically more informative, improved, and practical. MEF make it probable on behalf of ordinary LDR devices to replicate images of HDR. Similar to HDR imaging method, MEF doesn't need CRF assessment along with exposure settings. In addition, MEF can directly obtain data from ME images in addition to replicate the fused image with high-quality contrast in addition to bright colours. Along with this, the image which is fused achieved on account of MEF procedure can be shown on the LDR devices directly and doesn't need extra processing at all. Owing to all the aforesaid features, MEF methods are known to be additionally effective compared to HDR in expressions of computational complexity, speed, along with various metrics [4]. In, MEF methods, inputs are considered at various durations in various light environments. Once the images are taken, the objects which are in motion come into view that can cause ghosting artifacts in a image which is obtained by fusion. A ghosting artifact is a difficult concern in MEF methods. Various methods [4– 13] on MEF are suggested to create a premium, improved, and images which are perceptually pleasing than any of the input images.

Our Contribution:

- To produce a ghost-free HDR image from multiple images
- To enhance the QoS for HDR Images.
- To compare the suggested procedure with the existing.

The study is prearranged as; second part gives a literature survey. Third part illustrates research methodology and fourth section depicted proposed algorithm. Section 5 provides the results and discussion and comparison of results with existing methods and concluded the paper in section 6.

2. LITERATURE REVIEW

Hayat et al, (2019) projected a ghost-free MEF procedure by means of a dense SIFT descriptor in addition to a guided filter. The outcomes suggested that the offered scheme produced images of good excellence with usual cameras along with with no ghosting artifact. To perform this, descriptor was utilized for taking out local contrast data of source. While, for DS, HE and median filtering were preferred for computing color dissimilarity characteristic. Local features were considered on behalf of estimating the initial weights which contained discontinuities. Hence, a guided filter was preferred for eliminating noise along with irregularity in initial weights. Lastly image integration was achieved with pyramid decomposition technique. Investigational outcomes showed the advantage of the suggested more over some previous advanced techniques [14].

Martorell et al, (2019) projected a new procedure for MEF. This procedure decomposed image patches by using discrete cosine transform (DCT). Coefficients from patches by means of dissimilar exposures were fused. The luminance in addition to chrominance of the various images was combined individually. The procedure modified to dynamic sequence so as to evade impacts of ghosts. The primary sequence was handled to be made stationary prior to the application of fusion. Experiments through many datasets revealed that this procedure achieved superior to advanced [15].

Shaikh et al, (2018) suggested an efficient technique for MEF of dynamic scene without ghost impact. This technique was separated into four stages, *viz.*, remapping of images, weight map generation, and fusion of exposure in addition to correction of color by means of contrast improvement. Investigational outcome revealed that the ensuing images produced with the support of this technique were free from ghost impact also has high-quality color along with contrast. In addition, significant issue was that computational complexity to get to the most wanted result was very less [16].

Wang et al, (2020) presented a MEF fusion model with three modules. Initially, a decomposition part changed an input raw HDR image into a group of LDR images. Next, a saliency region proposal system was utilized to create candidate saliency maps on behalf of every LDR image in the exposure group. Lastly, a fusion procedure on the basis of uncertainty weighting was utilized for creating overall saliency map for an input image through integrating an attained LDR saliency maps. Wide experimentations demonstrated that this model obtained greater concert than advanced techniques on existing HDR eye fixation databases [17].

Zhang et al, (2019) suggested a combined super-resolution and HDR imaging procedure rebuilt from MEF images at the same time. Experiments were made beneath static as well as dynamic prospect to authenticate the suggested approach robustness. Subjective in addition to objective estimations on behalf of different experimentations were offered for authenticating the efficiency of suggested super-resolution along with HDR reconstruction procedure [18].

Deng et al, (2017) recommended a method to condense the ME images in an effective manner. Then HDR image generation, in addition to MEF can be understood in the decoder. The ME images were prearranged by MV-HEVC and the inter-view redundancy would be well exploited by changing the strength of the reconstructed base view with the support of a precise intensity-mapping function. Compared to the scenario by encrypting the generated HDR image by means of HEVC range extension, investigational outcomes proved that the suggested method obtained improved coding efficiency [19].

Wang et al, (2017) suggested a robust HDRI algorithm which is a ghost-free through visual salience based bilateral motion recognition and stack extension on the basis of EF. For ghost regions recognition, visual salience was used for determining variations amid multiple images; bilateral motion recognition was used to enhance accurateness of labeling motion regions. For EF, the suggested method decreased the discontinuous of brightness through stack extension and discarded data of ghost regions to evade artifacts through fusion masks. The outcomes revealed that the recommended procedure removed ghost artifacts precisely over modern developments together with rank minimization-based technique and patch-based technique by 63.6% and 20.4% time savings averagely [20].

Seo et al, (2020) suggested a new hue-correction design for MEF. In a projected system, a combined image was generating through a MEF technique by means of SSLA. After that, the fused image was hue corrected with hue maximally saturated colors of HDR one generate from similar input images. Using investigational outcomes, proposed scheme efficiency was verified [21].

Fang et al, (2019) projected a new objective IQA model for MEF images. Initially, the images were decomposed by means of a laplacian pyramid, and every pyramid sub band was preferred to take out gradient as well as contrast features. Next, the structure inconsistency map amid every exposure in addition to picture which is fused to attain large changed along with small areas were binarized. Lastly, information theory adaptive pooling approach was utilized for uniting these quality scores from the separate areas. Investigational outcomes revealed that the recommended model could obtain greater performance compared to the advanced models intended for fused images [22].

3. RESEARCH METHODOLOGY

Existing MEF procedures possesses two major issues: the combination in a stationary picture along with elimination of ghost in a dynamic scene (DS). Almost all procedures are valid to static scenes, there be short of the robustness to DS. Fusion is obtained through optimize of global or local exposure quality separately; consequently by matching visual impacts of fused outcomes are impacted. Local over or underexposure cause through merely utilizing a global optimization comes into view in an image which is obtained by fusion process. Likewise, completed fusion concert is reduced through simply with a local optimization. In addition, the heavily underexposed pixels of a image which considered as reference are not naturally matching throughout ghost elimination procedure in a DS, as pixels could be noticed as outliers [23]. Because of absence of quality of priori exposure, loss of local particulars could happen in a image that obtained by fusion process.

Existing MEF procedures

Many previously available MEF procedures follow a weighted summation structure

$$y = \sum_{k=1}^{K} w_k x_k$$

Where K is level of exposure in sequence of source image and x_k stand for a co-located pixel in k^{th} exposure image, x_k is based on the procedure is a pixel otherwise patch wise technique. 'y' mentions to matching pixel or patch in a image which obtained by fusion Y. w_k is the weight and has information regarding perceptual importance of x_k in a procedure of fusion. x_k as well as y could furthermore be co-located transforms coefficients otherwise a group of adjacent coefficients in the methods of transform domain. The majority of currently using procedures vary in w_k computation in addition to the way it could adjust over space otherwise scale-based on content of an image. The above condition is preferred on behalf of deciding through a most of ME Fusion procedures, excluding there is awfully small conversation regarding why weighted summary is a fine way of combination with the way in which it is distant from optimality. An effective decomposition of Laplacian pyramid designed for binocular image fusion was suggested in [24]. This system was afterward useful to ME Fusion [25], [26].

An analogous decomposition method, specifically boosting Laplacian pyramid [27], was suggested for ME Fusion by way of weights found by well-exposedness, gradient direction, in addition to clear distortion-based saliency metrics. In [28] suggested a initial patch-wise MEF technique through directly selecting a patch through maximum entropy to build a image by fusion procedure. Afterward, in [29] advanced structural patch decomposition for MEF was recommended. In [30] the authors assumed a bilateral filter [30] to take out data of the edge that is subsequently summed up to a layer of base image for in depth improvement. In [31] they suggested a probabilistic mixture design via initially approximating a primary image with the highest visual contrast along with scene gradient, also subsequently to generate final image by way of reversals in image gradients concealed. One more conditional random field-based ME fusion technique suggested in [32], in which weights were found through local contrast along with saturation of color.

A better ME Fusion scheme was suggested in [33]. In [34] improved information of a specified combined image in quadratic optimized structure. Guided filter [35] used in [36] to manage a component of pixel saliency in addition to spatial constancy once building a combined image. Motivated with the truth which conventional edge preserving smoothing methods, a weighted guided image filter was used by [37] furthermore considered for ME Fusion. A variational proposal for ME Fusion was suggested in [38] through integrating color matching along with gradient direction data. In [39] estimated global as well as local weights of a ME Fusion procedure through gradient-based, contrast, maximization in addition to an image saliency discovery technique, correspondingly [39]. To conquer the misalignment issue cause with camera along with object movement, a number of procedures were recommended. Zhang et al. [40] preferred direction of gradient to distinguish the dominant background from the object which is in motion. Median filter was preferred to sieve out an object which is in motion in [41]. the authors in [42] Allowed a two-level aspect improving fusion design of an image to explanation for DS with openly detect as well as correct inconsistent pixels regarding to a selected reference image. the authors in [43] started camera as well as object movements in a source series by means of a patch-wise matching procedure. Weight for every patch was determined with a random walker technique [43].

4. PROPOSED METHODOLOGY

The major intention of this AMEF algorithm in this class removes all of objects which are in motion in a scene to approximate static background. One significant postulation is that for every pixel, more input exposures consider stationary part of a scene. Owing to supposition, deficient quantity of input exposure, dynamic background, and deformable-body movements with overlap areas amid exposure has an unenthusiastic effect on deghosting quality for this class of methods. The procedure begins with executing a change recognition that includes with a fixed threshold on an absolute dissimilarity of irradiance values in every color channel. Initial motion mask doesn't respect object boundaries. So that process initial mask as per object boundaries, images are initially over-segmented by means of SLIC super pixels.

The proposed AMEF algorithm could create certain visible halo artifacts in the region of sharp edges. This is due to the mean intensity weights possibly will not produce smooth enough transitions across exposures close to strong edges.

Certain artifact could be decreased by adding additional constraints that support mean intensities of neighboring exposures to be utilized for fusion. One more solution is to widen MEF to a multi-scale design that used before to decrease the halo artifacts in HDR imaging and MEF. Otherwise, the collection of the reference image is significant for MEF to bring satisfactory deghosting outputs, as in numerous HDR reconstruction and MEF techniques.

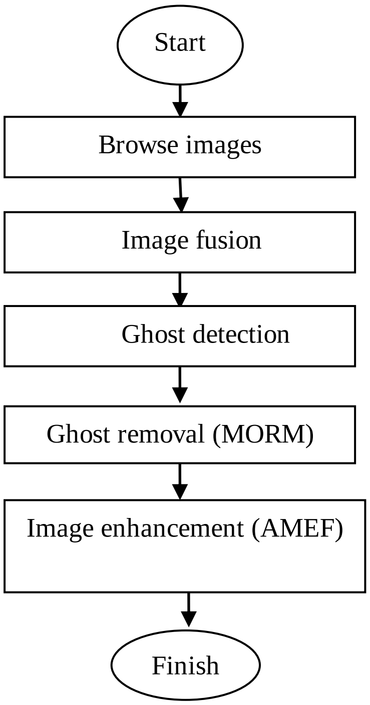

Figure 1: Proposed method flowchart

Proposed AMEF Algorithm:

- Initially, we browse image from dataset.
- Apply image fusion to fuse all the images of different exposure.
- Detect ghost from the fused image.
- Remove ghost from that image with the help of moving object removal method (MORM).
- Image enhancement by using AMEF.
- Calculate parameter PSNR SSIM and TIME.

5. RESULTS AND DISCUSSIONS

This part describes the outcomes and discussion of proposed methodology. Initially, the code will be run in the MATLAB and these following outcomes are acquired for the suggested technique. We preferred five dataset images (SculptureGarden, ReadingMan, Office, ArchSquence, Square and lady datasets) to verify the effectiveness of the recommended technique and to achieve results.

1. Input

Figure 2(a): SculptureGarden dataset

Fig 2(b): ReadingMan

Fig. 2(c): Office

Fig 2(d): ArchSquence

Fig 2(e) Lady

Fig 2(f): Square

Fig 2: Different exposure images of different dataset images

The above figure 2 shows the images of different datasets such as SculptureGarden, ReadingMan, Office, ArchSquence, square and lady datasets. In figure 2, image 1, 2, 3 are the images took at various exposures which we consider in this study for the analysis.

2. Image fusion along with detection of ghost and de-ghosting

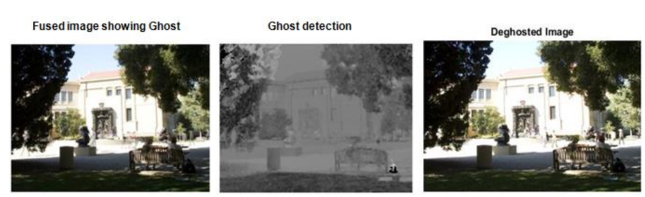

Figure 3(a): SculptureGarden dataset

Figure 3(b): ReadingMan Dataset

Figure 3(c): Office Dataset

Figure 3(d) ArchSquence dataset

Figure 3(e) Lady Dataset

Figure 3(f) Square Dataset

Figure 3: Images showing image fusion along with detection of ghost and de-ghosting by using MORM for images of different datasets

Figure 3 represents image fusion procedure of all the three input images that is image 1, image 2 and image 3 of different datasets. HDR images possibly will be made by the capture of numerous images of a scene with varying exposures. Images took in this manner are open to ghosting artifacts, which come into view if there is motion in a scene at the time of capture or during the fusing of the images. The detection of the ghost from the fused image also showed in figure. Observing the results presented in Figure 3, it is obvious that the enhanced deghosting outcomes are produced by Moving Object Removal Method (MORM) method. It may appear that there are no ghost artifacts as showed in the above figure.

3. Image enhancement

a. Histogram Equalization (HE)

HE is a method to adjust image intensities to improve contrast or it is a computer image processing method preferred to get better contrast in images. It achieves this with efficiently disperse the majority of repeated intensity values, i.e. stretching out the intensity range (IR) of an image. This technique generally boosts the global contrast of images once its functional data is representing by close contrast values. This permits for regions of lower local contrast to attain a high contrast.

Histogram is a graphical depiction of intensity distribution of an image. In easy terms, it showed quantity of pixels for every intensity value preferred. The outcomes of histogram depiction on the deghost image and its histogram representation is exposed in figure 4.

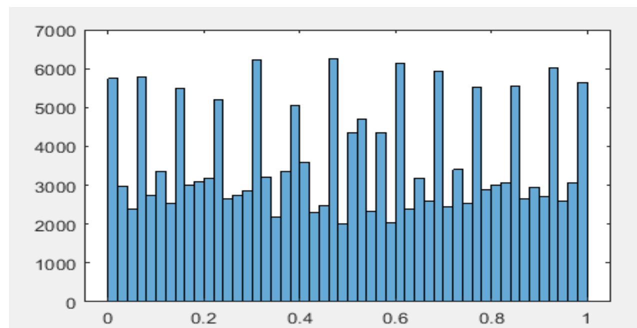

Figure 4: Histogram representation of the deghost image

b. Contrast Limited Adaptive Histogram Equalization (CLAHE)

It varies from AHE in its contrast restrictive. In CLAHE, contrast restrictive process is useful near every neighborhood from which a transformation function is resulting. CLAHE is advanced to avoid over strengthening of noise that AHE may produce. The output image of CLAHE on the deghost image is exposed in figure 5.

c. Contrast Stretching

It is an easy improvement method for image which efforts to enhance contrast in an image with 'stretching' IR value it has to cover a preferred range of values, full-range of pixel value that an image type concerned permits.

Figure 5(a): SculptureGarden dataset

Figure 5(b): ReadingMan Dataset

Figure 5(c): Office Dataset

Figure 5(d): ArchSquence dataset

Figure 5(e): Lady Dataset

Figure 5(f): Square Dataset

Figure 5: Image enhancement of existing methods and proposed AMEF method for different dataset images.

Output image of contrast stretching on a deghost image is exposed in figure 4. This below figure 5 illustrate an enhancement of HDR image by means of AMEF technique for different datasets which provides improved output than the existing HE, CLAHE and contrast stretching techniques.

5.2. Performance metrics

1. **Peak Signal-to-Noise Ratio (PSNR)**

PSNR is an estimation of peak error for a ratio amid the highest power of signal to power of noise that measured in dB. This relation is often preferred as an image quality measurement amid the original image as well as a compressed image. It is predictable from the mean squared error (MSE) and offers a good estimation of overall image quality. The higher PSNR values deduce a closer similarity between the original and reconstructed image. It is accurately termed as follows:

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \quad (1)$$

Where, R defines the highest probable pixel value of image.

2. Structural Similarity

SSIM is "a metric associated with quality of image and is used for assessing the impact of following visual features of an image: luminance, contrast and structure". Overall index is obtained as a multiplicative integration of these terms. SSIM is determined with following Equation 2:

$$SSIM(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma} \quad (2)$$

Where

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2+\mu_y^2+C_1},$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2+\sigma_y^2+C_2},$$

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y+C_3},$$

Where μ_x, μ_y, σ_x, σ_y, and σ_{xy} stands for local means, standard deviations, and cross covariance for images x, y.

5.3. Validation

The below given table 1 and 2 represents the validation tables of deghosting and enhancement techniques of existing and proposed techniques for different datasets.

From table 1, it is obvious that an existing approach preferred for the validation is MEF and the proposed deghosting technique for removing the ghost is MORM. From table 1, it is obvious that outcomes of PSNR, SSIM and processing time for various datasets of the proposed MORM are enhanced compared to the existing MEF technique.

In table 2 it is obvious that an existing system preferred for the validation is HE, CLAHE and contrast stretching and the proposed image enhancement technique for HDR is AMEF. From table 2 it is obvious that outcomes of PSNR and SSIM of proposed technique are enhanced than previous techniques [45]-[47] for various datasets

6. CONCLUSION

In this study, an Advanced MEF was suggested for an enhancement of HDR images. A Moving Object Removal Method was used to eliminate ghost in fused image. Main objective of the study is to generate a ghost-free HDR image from multiple images then also associated the achieved outcomes of the suggested method with the previous algorithms like HE, CLAHE and contrast stretching. From the achieved results it is showed that the results of AMEF is enhanced compared to the existing techniques.

Table 1: Deghosting Techniques

Image	**PSNR**		**SSIM**		**Processing time**	
	Existing (MEF)	**Proposed (MORM)**	**Existing (MEF)**	**Proposed (MORM)**	**Existing (MEF)**	**Proposed (MORM)**
Square	64.5406	76.0121	0.6029	0.3887	1.543507	0.485412
Lady	64.9804	77.1124	0.7504	0.5585	0.566132	0.221693
Reading man	62.6834	74.1666	0.4445	0.3029	0.54082	0.227622
Arch	68.6036	78.6870	0.9114	0.6602	0.633971	0.247710
Office	64.1967	76.5752	0.4491	0.2838	0.534751	0.268442
Sculpture Garden	68.8072	82.5072	0.9603	0.8792	0.487690	0.270645

Table 2: Image Enhancement Techniques

Parameter	**Square image**				**Lady image**			
	HE [44]	CLAHE [45]	Contrast Stretching [46]	**AMEF (proposed)**	HE	CLAHE	Contrast Stretching	**AMEF (proposed)**
PSNR	78.45	76.1529	76.0156	**81.9490**	78.5463	77.3049	77.1579	**83.7204**
SSIM	0.4472	0.3409	0.3886	**0.9301**	0.6371	0.5629	0.5601	**0.9963**
Computing Time	0.672233	2.015983	1.897656	**0.996454**	0.486177	1.136943	1.15423	**0.910976**

Parameter	**ReadingMan image**				**Arch image**			
	HE	CLAHE	Contrast Stretching	**AMEF (proposed)**	HE	CLAHE	Contrast Stretching	**AMEF (proposed)**
PSNR	76.4160	74.2410	74.2680	**82.4988**	79.7662	82.1745	81.7466	**83.2563**
SSIM	0.2593	0.2698	0.2814	**0.8833**	0.7328	0.8748	0.8098	**0.9805**
Computing Time	0.304681	0.659891	0.764538	**0.779044**	0.457193	0.849271	0.795674	**0.881194**

Parameter	**Office image**				**Sculpture Garden image**			
	HE	CLAHE	Contrast Stretching	**AMEF (proposed)**	HE	CLAHE	Contrast Stretching	**AMEF (proposed)**
PSNR	77.1809	77.2768	76.9696	**84.6164**	76.6824	82.9104	82.3659	**82.8021**
SSIM	0.4472	0.3028	0.2934	**0.9811**	0.6065	0.8666	0.7876	**0.9655**
Computing Time	0.288159	0.678104	0.718687	**0.789953**	0.333818	0.648046	0.648756	**0.812304**

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