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MULTI-EXPOSURE IMAGE FUSION USING MULTI SCALE DECOMPOSITION

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ABSTRACT:
Modern computational photography methods have made significant progress in overcomingthe limitations of conventional digital cameras in handling scenes with a wide motion scope, among them isHigh Dynamic Range (HDR) photography. Due to constrained motion scope of commonly used imagerecorders, it is challenging to capture all the details of real scenes in a single image. To lessen this problem, acollection of pictures at different exposure conditions could be used to capture the scene, then via image fusion, combined into a useful image.MEF(multi-exposure image fusion)is a type of image fusion technique that combines many photos of the same scene captured with various exposure settings. Due to the significance of creating high-dynamic range photographs, MEF techniques have attracted a lot of interestlately. According to previous study, multi-scale structural-patch-decomposition-based MEF (MSPDMEF) provides the greatest fusion quality and the shortest runtime, but it suffers from detail loss. To address this problem, we first incorporate edge-preserving factors into our approach in order to preserve the fine features in the fused pictures in a single course.

Keywords:
Multi exposure image fusion, patch decomposition, Edge preserving, Quality

INTRODUCTION

Greater ranges of brightness are captured by HDR photography than by ordinary cameras. A popular and straight forward method for creating HDR pictures is multi-exposure image fusion (MEF). Additionally,MEF has the ability to improve low-light pictures, remove haze, and identify salient areas. A decent MEFtechnique should function effectively in both static and dynamic settings while utilizing the least amount of computational power possible, making it appropriate for mobile devices. Zhangetal. and Maetal. created the cutting-edge technique known as Structural Patch Decomposition Multi-Exposure Image Fusion. To create a high dynamic range picture with less noise, it combines multiple images captured at various exposure levels using structural patch decomposition. In high dynamic range imaging, this technique is especially helpful for capturing a broad variety of brightness levels.Halo effects and false edges are examples of artifacts that can appear in the decomposed picture as a result of SPD. It may become more difficult to compute and require more parameter tweaking to mitigate theseartifacts.

By conducting image decomposition at various scales and reducing parameter dependence, MSPD improves on SPD. However, it has draw backs like higher computational costs and a chance of over-smoothing, which can result in detail loss in the fused image. We suggest a method known as the multi-scale decomposition approach to overcome the loss of details in the fused picture, in which we can maintain more detail information of the fused image by incorporating edge preserving components.

LITERATURE SURVEY

This section provides an overview of existing MEF algorithms with a focus on the various methods used to combine perceptual weights for fusion and the properties that are designed to be independent of exposure when calculating motion.

Hui Li et al [1], Fast multi-scale structural patch decomposition is a technique that decomposes large images fast by rapidly analyzing patches at different scales. It is commonly combined with other image processing techniques for object identification, feature extraction, and segmentation. However,it has draw backs, such as the possibility of unreliable results from under or over segmentation, and it might not retain fine image details as it concentrates more on general structural data.

A structural patch decomposition technique was put out by Kede Ma et al. [2] to combine severalimages of the same scene taken at varied exposure levels. The procedure partitions the images into patchesand assigns weights to each piece based on structural information. Although the final fused picture keepsdetails in both bright and dark areas, the process can be computationally costly and could produce artifacts in regions with different exposure or noise levels.

TszNam Chanetal[3],technique uses perceptual evaluation to assess the visual quality of composited images made from multiple exposures. Based on a variety of perceptual criteria,human observersassess the merged image's quality, providing a detailed examination of image quality that corresponds to human perception. The generalizability of this technique is constrained, and it can be time-consuming and subjective.

Hybrid learning, a technique to improve an image's brightness and contrast using multi-scale exposure fusion, was suggested by Chaobing Zheng et al [4]. It uses supervised and unsupervised learning strategies to fine-tune the fusion algorithm's settings, enhancing accuracy and robustness in the process. This method can be applied to a variety of industries, but it can take a while and specialized equipment or software to produce high-quality outcomes.

In order to rapidly combine multi-exposure images, Kede Ma, et al [5] method suggests using a deep convolutional neural network. High-speed photography and real-time video editing can both benefit from the method's improved brightness, contrast, and detail. However, to train and implement the model using this technique, you need a sizable training data set as well as expensive hardware and software.

METHODOLOGY:

Multi-scale decomposition using Laplacian pyramid

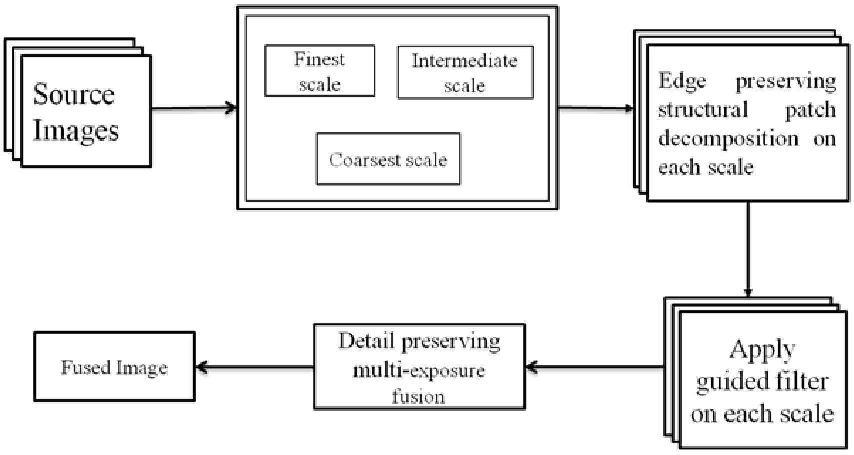

Fig1: Block diagram of proposed method

At the outset of the algorithm, an essential and critical step involves decomposing the input images into multiple scales using a Gaussian pyramid. This step is instrumental in creating a mult-scale representation of the input images, allowing the algorithm to capture and preserve the intricate details of the images at various scales. The Gaussian pyramid works by smoothing and down-sampling the images to produce a series of increasingly lower resolution images. This process creates a hierarchical

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structure that reflects the varying levels of details in the input images.
After this initial decomposition step, the algorithm moves on to perform edge-preserving structural patch decomposition on each scale. The purpose of this decomposition is to separate the images into small, spatially coherent regions or patches, and to group these patches based on their structural similarity. This technique is particularly useful in preserving the fine details of the input images, while also reducing the impact of noise and artifacts that can often corrupt images.
Once the patches have been separated and grouped, the algorithm proceeds to perform exposure fusion on each scale separately. This step involves combining the input images by selecting the best pixels from each image to create a single, unified output image for that specific scale. This process is designed to produce images that exhibit a higher dynamic range and greater visual appeal than the original input images.
In summary, the algorithm operates in a series of steps that involve decomposing the input images into multiple scales, performing edge-preserving structural patch decomposition, and finally performing exposure fusion to create a unified output image. The combination of these steps enables the algorithm to create images that exhibit a higher level of detail and clarity, while also reducing the impact of noise and artifacts that can often degrade image quality.

RESULTS AND DISCUSSION:
QUALITATIVE ANALYSIS:
From below qualitative analysis, we can observe that the final fused images that are obtained from the existing methods are less enhanced compared to the multi-scale decomposition method based multi exposure image fusion.
The methods that we compared are: Structural patch decomposition based Multi exposure image fusion (SPD-MEF) by [Kede Ma, et al], and Fast multi-scale Structural patch decomposition based multi exposure image fusion (MSPD-MEF) by [HuLi,etal].
The final fused image we obtained retains more details with preserved edges than the images obtained by the
previous existing methods.

Table 1: Comparison of different data sets with existing methods and proposed method

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SourceS equence	SourceImages			FusedImage		
	1	2	3	SPD-MEF	Fast multi-scale SPD-MEF	Proposed Method
Garden						
Horse						
Arno						
House						
ArchS equence						
Tower						

QUANTITATIVE ANALYSIS:

From below quantitative analysis we can see that the metric values of the previously existing methods are less compared to the edge-preserving, multi-scale decomposition method. Usually metrics are used to evaluate how will an image processing method performs in comparison.

The metrics included are:

MEF_MS_SSIM (Multi-scale Structural Similarity Index): In this, SSIM index between the MEF image and each source image in the source sequence at various scales is used to compute the MS-SSIM index. The final step is to calculate the overall MS-SSIM index by adding the separate SSIM indices from each scale using a weighted geometric mean.

Table 2: Quantitative value for SSIM metric

Source sequence	SPD-MEF	Fast Multi-scale SPD-MEF	Edge Preserving SPD-MEF
Garden	0.9989	0.9998	0.9997
Horse	0.9984	0.9997	0.9998
Arno	0.9987	0.9999	0.9998
House	0.9982	0.9996	0.9997
Arch Sequence	0.9990	0.9992	0.9999
Tower	0.9986	0.9997	0.9998

The SSIM index is calculated as follows:

$SSIM(m,n)=$

$$(2\mu_m\mu_n+D1)(2\sigma_{mn}+D2)(\mu_m^2+\mu_n^2+D1)(\sigma_m^2+\sigma_n^2+D2)$$

Where:

- m and n are the two images being compared
- μm and μn are the means of x and y respectively
- σm and σn are the standard deviations of x and y respectively
- σmn is the cross-covariance between x and y
- D1 and D2 are constants added to avoid division by zero.

Table 3: Quantitative value for PSNR metric

ImageSequence	SPD-MEF			FastMulti-Scale SPD-MEF			EdgePreservingSPD-MEF		
	1	2	3	1	2	3	1	2	3
Garden	10.511	18.026	9.860	15.522	20.146	10.011	18.062	15.770	10.277
Horse	9.348	14.901	12.603	9.389	10.146	13.824	9.479	15.814	13.705
Amo	9.235	15.482	12.059	7.638	18.320	12.162	8.994	16.927	13.612
House	5.679	9.396	15.021	5.897	8.596	11.201	6.007	9.202	15.179
ArchSequence	11.460	12.031	16.923	11.497	14.497	17.497	12.105	14.175	18.059
Tower	10.113	12.462	12.719	18.833	12.550	10.891	18.960	14.209	10.793

The next metric is PSNR (Peak Signal to Noise Ratio): PSNR is a widely used measure to assess an image's or video's quality.

$$PSNR=10\log10((MAX^2)/MSE)$$

Where:

- MAX is the highest pixel number that the image can have. (for example, 255 for 8-bit images)
- MSE is the mean squared error between the original image and the compressed image.

MSE is calculated as:

$$MSE = \frac{1}{M} \times \sum_{a=1}^{M} [I(a,b) - K(a,b)^2]$$

Where:

- M is the total number of pixels in the image
- I(a,b) is the pixel value of the original image at position(a,b)
- K(a,b) is the pixel value of the compressed image at position(a,b).

Therefore, they have less noise or distortion than the original picture, images with higher PSNR values are generally of higher quality.

CONCLUSION:

In this study, we used a multi-scale decomposition technique with edge preservation that allows for multi-exposure fusion, by incorporating edge-preserving factors, which can preserve more details in the fused images. In comparison to the state-of-the-art methods, SPDMEF and MSPD-MEF, our method can inherit allof their benefits, such as the suppression of halo artifacts, avoidance of the ghosting effect, and fastest running time, while also overcoming their weakness, namely detail loss. Therefore, the extensive experiments confirm that, when compared to various MEF methods, the current method can achieve the most cutting-edge visual quality for both static and dynamic scene settings. This strategy works better than the several image fusion techniques in terms of both subjective and objective quality metrics. In addition, the suggested approach is effective and adaptable, making it appropriate for use in real-world applications in industries like photography, computer vision, and medical imaging.

FUTURESCOPE:

The technique used in this paper is intended for single-image multi-exposure merging. It would be intriguing to apply it to video processing. In order to do this, the algorithm may need to be modified to operate withMtemporal sequences of images, or novel methods for combining multiple frames into a single output may need to be developed.

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