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Improving Quality Measure of Multi-Exposure & Multi-Modal Data using Improved Fusion

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Abstract— Here in this paper a new and efficient technique for the Fusion of Multi-Exposure and Multi-Modal Image Dataset for improving the Perceptual Quality Assessment of Images. The Existing Structural Similarity based Image Fusion for the Fusion of Multi-Exposure image doesn't provide effective Fusion of Images and hence Low Structural Similarity and Perceptual Quality Measure, hence the proposed methodology implemented here using Contrast Enhancement and Canny Edge Detection and Smoothning is implemented which provides high Perceptual Quality measure in Comparison.

Index Terms— Image fusion, Single-Sensor Image Fusion (SSF), Multi-Focus Image Fusion (MFF), Pixels, Standard Dynamic Range (SDR), high-dynamic range (HDR), Image Quality Assessment.

I. Introduction

Image fusion is the process that combines information from multiple images of the same scene. The image fusion may result a new image that preserves the most enviable information and characteristics of every input image. The main function of image fusion is grouping of gray-level high-resolution panchromatic image and colored low-resolution multispectral image. The standard fusion methods perform well spatially but typically introduced spectral distortion. These images were clicked from various sensors, obtained at different times, or having unusual spatial and spectral characteristics. The objective of the image fusion is to maintain the most attractive characteristics of each image. With the accessibility of data in numerous fields, image fusion has been getting growing attention in the researches for an extensive spectrum of applications.

In current years, a number of computational image fusion superiority assessment metrics have been suggested [1], [2]. Metrics that accurately relate to human observer performance are of great value but are very difficult to design and, thus, are not yet available at present.

Image fusion is a method of attaining images by high spatial and spectral resolution commencing low spatial resolution and high spatial resolution images. There is frequently an opposite relationship among the spectral and spatial resolution of the image. Because of the requirement for higher classification accuracy and the need in improved positioning correctness there is always a want to better the spectral and spatial resolution of remotely sensed imagery. The primary goal of the disclosure fusion is to protect details in both very dark and tremendously bright regions exclusive of HDRI representation and tone mapping step. The fundamental idea of diverse exposure fusion approaches [4], [5], [6] and [7] is based on the utilization of different local measures to generate weight map to preserve details present in the different exposures.

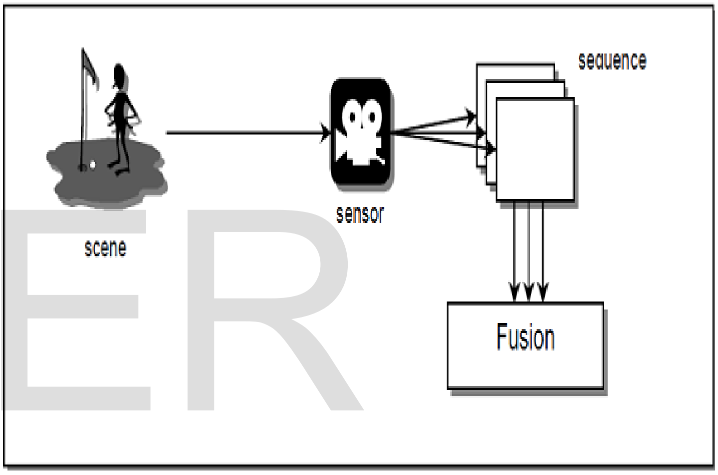

Fig. 1: Single Sensor Image Fusion System [3]

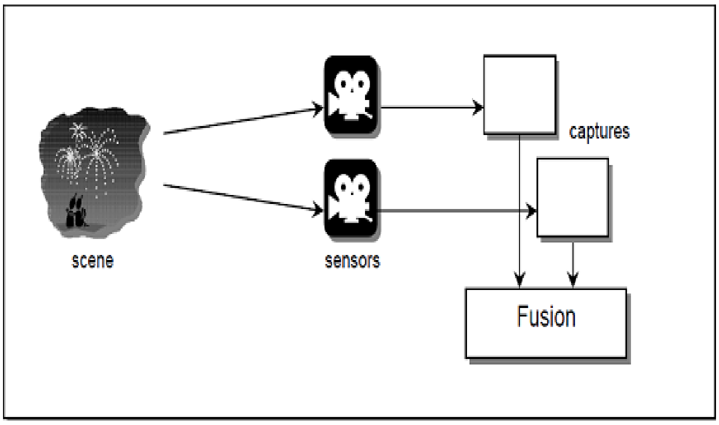

Fig. 2: Multiple Sensor Image Fusion System [3]

It begins by presenting a classification of the different techniques. The classification is based on which target object

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the different methods focus on. The easiest technique for image fusion is pixel-by-pixel [10] gray level average of the source images except this way leads to objectionable side effects such as reduced contrast. In the modern years, numerous image fusion methods had been offered like statistical [11] and hue-saturation- intensity (HSI) method, numerical methods, principal component analysis (PCA) method [8][9][12].

Image fusion algorithms can be classified into different levels: low, middle, and high; or pixel, feature, and symbolic levels respectively. The pixel-level technique works either in the transform domain or in the spatial domain. The requirement for such an operation is that images have been obtained by homogeneous sensors, such that the images reproduce parallel or analogous physical properties of the scene. The fusion techniques, for instance the Brovey method, principle component analysis (PCA) [16], averaging, and HSI based methods descend under the spatial domain approaches. The feature-level algorithms usually segment the image into adjacent regions and fuse the regions collectively using their properties. The features used may be calculated separately from each image or they may be obtained by the simultaneous processing of all the images. Piella suggested numerous activity level measures including the median, the absolute value, or the distinguish to neighbors measures [13].

Fusion using discrete wavelet transforms (DWT) method: In the DWT-based fusion method, the source images are first transformed by DWT to their corresponding wavelet coefficient images at every scale level. Consequent approximation coefficients and detail coefficients of the source images at each level are then complex correspondingly based on a convinced fusion rule. This rule can be a straightforward addition or averaging, or a PCA-based weighted averaging. The fused approximation and detail coefficients at each level are used in the final reconstruction of a single output fused image by an inverse DWT [14-15].

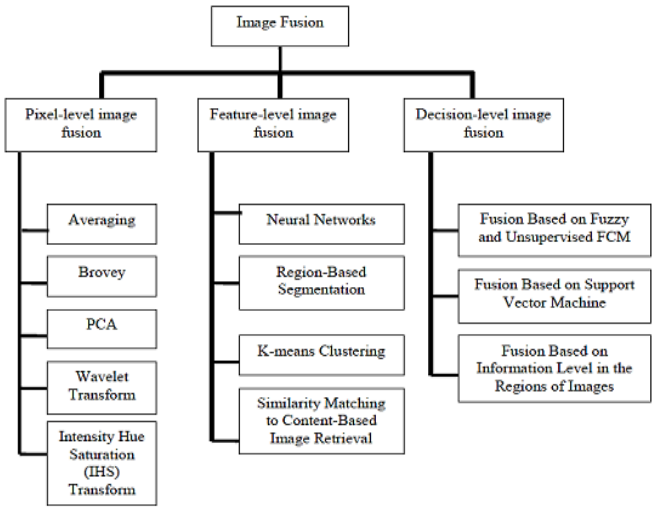

Fig: 3 Level classifications of the diverse popular image fusion methods based on the computation source.

II. Literature Survey

The Principle Component Analysis image fusion methods [16] essentially uses the pixel values of all source images at every pixel location, adds a weight factor to every pixel value, and take an average of the weighted pixel values to manufacture the result for the fused image at the identical pixel location. The optimal weighted factors are indomitable by the PCA procedure. The PCA image fusion process eliminates the redundancy of the image data.

It is a branch of image fusion for bandwidth extrapolation ahead of the limits of a conventional electronic image system [17]. Katartzis and Petrou express the core principles of SR reconstruction and make available an impression of the most diplomat methodologies in the domain.

Mitianoudis and Stathaki express the competence of a transform assembled using Independent Component Analysis (ICA) and Topographic Independent Component Analysis based for image fusion presented in their work [18]. The bases are qualified offline with images of analogous context to the experiential scene. The images are combined in the transform domain via new pixel-based or region-based rules. An unsupervised adaptation ICA-based fusion method is also commencing.

Li and Yang firstly explain the standard of region-based image fusion in the spatial domain [19]. Then two region-based fusion methods are recommended. They suggested a spatial domain region-based fusion technique with fixed-size blocks. Investigational results from this method are hopeful. More exclusively, in malevolence of the primitiveness of the segmentation methods employed, the results achieved from this fusion processes that consider explicit feature information regarding the source images, are outstanding in terms of visual perception.

The authors presented a number of algorithms of fusion based on multi-scale Kalman filtering and computational intelligence methodologies [20]. The proposed algorithms are applied to two kinds of problems: a remote sensing segmentation, classification, and object detection application performed on real data obtainable from experiments and a non-destructive testing/assessment problem of fault detection with electro-magnetic and ultrasound recordings.

In this proposed work, [21] they propose a novel explicit image filter known as guided filter. This filtering output is locally a linear transform of the guidance image. On one hand, the guided filter has excellent edge-preserving smoothing properties approximating the bilateral filter, but it does not experience from the gradient reversal artifacts. Alternatively, the guided filter can be employed afar smoothing using guidance image it can formulate the filtering output more structured and fewer smoothed than the input.

In this proposed work [22] they describe a Discrete Wavelet Transform (DWT) can be used for merging the lower frequency component of a multi-spectral image and its higher spatial resolution images by means of rules. Then, using DWT fused image can be used to the spectral post processing such as classification which leads to more accurate and précised results.

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III. PROPOSED METHODOLOGY

1. Take two images which need to be fused and filtered.
2. Apply DWT transformation of the input image.
3. Investigation of the Dominant brightness level of the LL band of the DWT is executed out.
4. Image Decomposition of image due to the dominant brightness level is carried out.
5. Concern Adaptive intensity transfer functions on dissimilar intensity levels of the decomposed image and then smoothened out.
6. Smoothen image is conceded to the canny edge detection techniques which is subsequently integrated through the Contrast enhancement techniques and is segmented out.
7. The inverse DWT is applied after that to the fusion image and HH, HL, LH bands to get the contrasted image.
8. Now the two enhanced contrast image can be fused to get the result fused image.

The proposed methodology implemented here provides efficient fusion as compared to the existing fusion techniques. The main reason behind the efficient fusion is enhancement of the image and the fusion of the two images using canny edge detection. The source images can be enhanced by applying DWT transformation and finding the pixel region having low intensities. The image when enhanced can be fused with the pixel regions with high intensity values.

DWT TRANSFORMATION

Apply DWT algorithm of level 2 in which we have applied HAAR wavelet transformation and can be given as:

```
cH = cell(1,no_of_Level);
cV = cell(1,no_of_Level);
cD = cell(1,no_of_Level);
for iLevel = 1:no_of_Level,[cA{iLevel},cH{iLevel},cV{iLevel},
cD{iLevel}] = dwt2(original_image,'haar');
end
dwtimage = dwt2(original_image,'haar');
fast_ftkernel = dwt2(kernelimage,'haar');e
fast_ftkernel(find(fast_ftkernel == 0)) = 1e-6;
fast_ftblurimage = dwtimage.*fast_ftkernel;
blurimage = idwt2(dwtimage,cH{iLevel},cV{iLevel},cD{iLevel}
,'haar');
```

CANNY EDGE DETECTOR

Canny edge detection method finds edges by looking for local maxima of the gradiant of f(x, y). Here the gradiant value is computed using the derivative of a Gaussian Filter. The approach used here will takes two thresholds to find strong and weak edges, and contain the weak edges in the output only if they are connected to strong edges. Therefore, this approach is additional likely to detect true weak edges.

1. Allocate region seeds si for each region I
2. Calculate ui(x,y): the probability of first arriving sifor a random walker starting from (x,y)

3. Assign (x,y) to Label k if uk(x,y) is the largest among ui(x,y) for i= 1…N

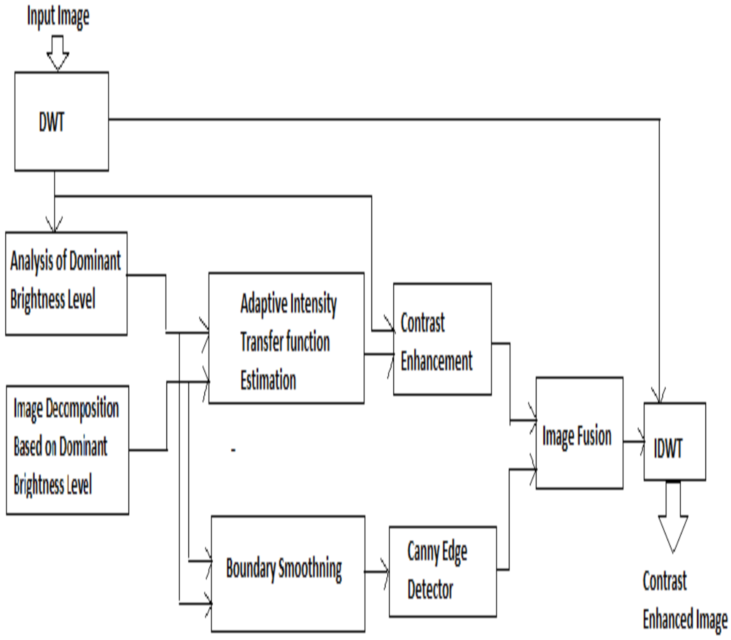

Figure 4 Outline of the Proposed Work

As shown in the above figure is the outline of the proposed technique. The proposed techniques contains transformation of image using DWT whose low sub band value is used for the improvement of the level of brightness and its contrast can be enhanced which is smoothed out and the canny edge detector is used for the sharpness of the images pixel boundaries and this images get fused with high sub band values to get contrast improved image.

The canny edge detector is used for the improvement of images edges which is hard to smoothen using other technique, hence using canny edge detector is used for the better smoothen of the images which is then fused with the other part of the images so that the overall effect of the image gets smoothen.

FUSION

```
[A1L1,H1L1,V1L1,D1L1] = swt2(im1,1,'sym2');
[A2L1,H2L1,V2L1,D2L1] = swt2(im2,1,'sym2');
[A1L2,H1L2,V1L2,D1L2] = swt2(A1L1,1,'sym2');
[A2L2,H2L2,V2L2,D2L2] = swt2(A2L1,1,'sym2');
AfL2 = 0.5*(A1L2+A2L2);
D = (abs(H1L2)-abs(H2L2))>=0;
HfL2 = D.*H1L2 + (~D).*H2L2;
D = (abs(V1L2)-abs(V2L2))>=0;
VfL2 = D.*V1L2 + (~D).*V2L2;
D = (abs(D1L2)-abs(D2L2))>=0;
DfL2 = D.*D1L2 + (~D).*D2L2;
D = (abs(H1L1)-abs(H2L1))>=0;
HfL1 = D.*H1L1 + (~D).*H2L1;
D = (abs(V1L1)-abs(V2L1))>=0;
VfL1 = D.*V1L1 + (~D).*V2L1;
D = (abs(D1L1)-abs(D2L1))>=0;
DfL1 = D.*D1L1 + (~D).*D2L1;
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AfL1 = iswt2(AfL2,HfL2,VfL2,DfL2,'sym2');
imf = iswt2(AfL1,HfL1,VfL1,DfL1,'sym2');

IV. Result Analysis

The table shown below is the Analysis of the existing work. The Analysis is done on the mutliexposure dataset with a number of result parameters including time, measure of enhancement, Normalized Mutual Information, Structural Similarity, Phase Congruency and Quality metrics.

Image	Time	Qmi	SS	PC	Qc
Image-1	3.1136	6.2509	0.44632	10.0330	0.6899
Image-2	1.444	1.7572	0.4760	4.3810	0.7256
Image-3	1.3196	0.3304	0.2976	0.7080	0.5404
Image-4	5.6408	0.1139	0.6190	2.8278	0.8174
Image-5	0.6800	17.2106	0.4638	10.2931	0.7098
Image-6	0.8516	NA	0.2006	0.0190	0.4683

Table 1 Result Analysis of Existing work on Multiexposure Dataset

The table shown below is the Analysis of the Proposed work. The Analysis is done on the mutliexposure dataset with a number of result parameters including time, measure of enhancement, Normalized Mutual Information, Structural Similarity, Phase Congruency and Quality metrics.

Image	Time	Qmi	SS	PC	Qc
Image-1	0.3212	5.8176	0.2819	5.2271	0.4954
Image-2	0.2120	1.7572	0.3119	2.0899	0.5311
Image-3	0.1652	0.3304	0.1333	1.1303	0.3459
Image-4	3.8615	0.8625	0.4816	1.6253	0.6825
Image-5	0.2725	17.2106	0.2995	1.1303	0.5153
Image-6	0.6529	NA	0.0363	1.1303	0.2738

Table 2 Result Analysis of Proposed work on Multiexposure Dataset

The table shown below is the comparison of the existing and proposed work when applied on multifocus and multiexposure dataset. The Analysis also shows the performance of the methodology and the number if pairs on which the technique is applied.

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Source Image	Index	Existing work	Proposed Work
MultiExposure Dataset	Qy	0.5384(6)	0.6843(6)
	Qc	0.5483(4)	0.8654(4)
	Qp	4.5721(6)	7.79463(6)
	Qmi	1.4743(2)	2.4483(5)
MultiFocus Dataset	Qy	0.7653	0.8743
	Qc	0.5748	0.7641
	Qp	0.6431	0.8742
	Qmi	0.6612	0.7973

Table 3 Techniques applied on pairs.

V. Conclusion

The proposed methodology implemented here performs better fusion as compared to the existing technique of fusion of the source images. The comparison between existing and proposed work is done on the basis of various parameters such as Mutual Information, Covariance between two images, Structural Similarity, Computational Time and measure of enhancement of images. The proposed methodology can fused more pair of images as compared to the existing technique.

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