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Multi-focus Image Fusion Using Image Morphology

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Abstract

Image fusion is one of the emerging topics in image processing due to its applications in computer vision, military services, medical imaging, remote sensing and so forth. The cameras today have limited depth-of-field. So, in multi-focus image fusion, the images that have different focus areas are merged to produce the all in focus image. In this research work, a block based spatial image fusion algorithm is presented. In block based algorithm, finding a suitable block size is a problem, because it may vary from one image to another. Here, an effective quad tree structure is presented that decomposes the image into blocks only if it is required to do so. If one of the blocks of source images is fully focused and other is fully out-of-focus then fully focused block is copied to the fused image, otherwise the block pair is recursively divided. Also, the level, in quad tree structure, upto which the decomposition takes place is more in proposed algorithm. The algorithm is robust as it can work with any focus measures such as variance, EOMG, spatial frequency, etc. From the experiments carried out, proposed algorithm has comparatively better results of entropy, MSE, PSNR and edge based similarity metrics.

Key Words—*Image Fusion, Focus Measure, Multi-focus Image*

I. INTRODUCTION

Any piece of information makes sense only when it is able to convey the content in it with clarity. Image fusion provides this functionality. From the given input images, the more informative image is obtained with superior quality than any of the individual input images. The desired portion from the registered images is combined in the fused image.

In digital cameras, when lens focuses on objects at certain distance, all objects at that distance are sharply focused, and objects that are not at the same distance are out-of-focus and theoretically not sharp or we can say, blurred [6]. This means, the camera has limited depth-of-field.

Due to this limitation, it is usually impossible to acquire an all in focus image. But for human machine perception, we require an all in focus image. So, multi-focus image fusion is used to combine both images in which one part of the image is focused in one image and other part is focused in another image. So when we combine both images, we will get an all in focus image.

Image fusion is needed because the ability of camera to capture information is different from another. Even if we are using the same camera, the capture emphasis of it varies with imaging environment. Hence, we can take more than one image of the same scene at different optic condition at different time or from different device [5]. Then these images can be merged to get more informative image.

Image Fusion category

Image fusion can be categorized as Multi-view Fusion, Multi-modal Fusion, and Multi-focus Fusion.

In multi-view image fusion, the images of same modality are taken at same time from different places or under different conditions. This type of image fusion is generally used to make 3D effect.

In multi-modal image fusion, images of different modality are merged. For example, we can merge infrared and visual image or NMR and SPECT images from medical can be merged. In [2], Bai and Tu's method presents multi-modal image fusion using opening and closing morphology operators based toggle operator.

In multi-focus image fusion, images are divided into regions such that one part is focused in one image and other part is focused in another image. The resultant image will be focused everywhere.

Image fusion can be classified as spatial domain image fusion and spatial domain image fusion. In transform domain fusion, a transformation is performed on the source images, then the fusion is performed and finally, the fused image is obtained by applying an inverse transform.

Transform domain based method suffers from shift variance, that is if the scene does not remain steady during capturing or if there is a mis-registration in the source images then the performance of these techniques will significantly decrease [3]. This is because the transformation modifies the pixel values and these values are taken into consideration for fusing.

Spatial domain fusion overcomes the problem of shift variance; the pixel values are directly manipulated here. Spatial domain methods are classified as region based, block based and pixel based methods. The pixel based method considers the single pixel and use the information in the local neighbourhood. In region based method, the region of interest from the source images are found and fused to construct the resultant image. In block based method, the source images are divided for constructing the fused image. But finding suitable block size is a problem in this method [4]. The larger block will contain portion from both focused and defocused region so, there are chances for getting more defocused region. And small blocks will not vary much in contrast, so it becomes difficult to choose from both regions, and small regions will also be affected by pixel mis-registration problem [4].

General process for multi-focus image fusion

The requirement for image fusion is that, the images to be fused must be registered. So, initially, we take the registered source images and detect the focused part from each of the source images. The general assumption for multi-focus image fusion is that, focused part will appear sharp than the defocused part [1]. There are different focus measures using which we can find the focus of particular area, block or region. The commonly used focus measures are, Energy of Gradient (EOG), Sum of Modified Laplacian (SML), Spatial Frequency, Tenenbaum Gradient (Tenengrad), variance, etc.

After the focused part is detected, it is merged for constructing the fused image, which is more informative than any of the individual source images.

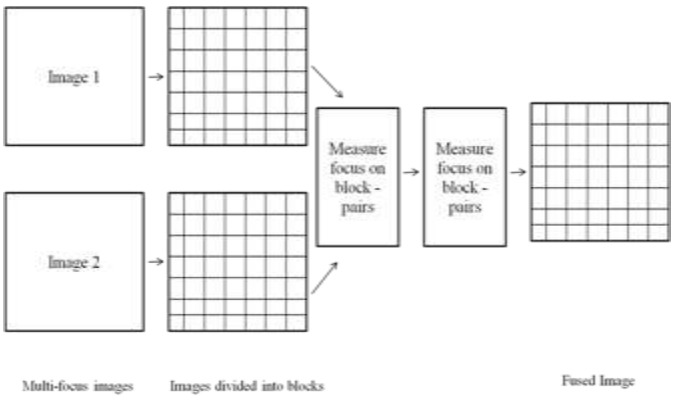


Fig. 1: A generic schematic diagram for multi-focus image fusion by computing the focus measure on equal-sized blocks [4]

Figure 1 shows general conceptual diagram of block-based image fusion method. Two source images A and B are divided into several blocks and the degrees of focus of each block are measured. After that, the composite image takes one block which has higher value of focus between source A and B. The performance of this block-based approach highly depends on the focus measure as well as the size of block.

Existing methods

There are different Focus Measures available like, Variance, Spatial Frequency (SF), Energy of Gradient (EOG), Tenenbaum gradient (Tenengrad), Energy of Laplacian (EOL), Sum of Modified Laplacian (SML) [7], etc. In [4], De et al. proposed energy of morphology gradient (EOMG).

1. Variance [7]

It is the simplest focus measure for grey scale image. For image f(x,y) of size M×N, variance is defined as follows:

$$variance = \frac{1}{M \times N} \sum_x \sum_y \left(f(x,y) - \mu \right)^2$$

Where, $$\mu = \frac{1}{M \times N} \sum_x \sum_y f(x,y)$$

2. Energy of image Gradient (EOG) [7]

$$EOG = \sum_x \sum_y (f_x^2 + f_y^2)$$

Where, $f_x = f(x+1,y) - f(x,y)$

And $f_y = f(x,y+1) - f(x,y)$

3. Tenenbaum's algorithm (Tenengrad) [7]

$$Tenengrad = \sum_{x=2}^{M-1} \sum_{y=2}^{N-1} [\nabla S(x,y)]^2$$ For $\nabla S(x,y) > T$,

Where T is threshold value, and $\nabla S(x,y)$ is sobel gradient magnitude value.

$$\nabla S(x,y) = [\nabla S_x(x,y)^2 + \nabla S_y(x,y)^2]^{1/2}$$

Where $\nabla S_x(x,y)$ and $\nabla S_y(x,y)$ are

$$\nabla S_x(x,y) = \{-[f(x-1,y-1) + 2f(x-1,y) + f(x-1,y+1)] + [f(x+1,y-1) + 2f(x+1,y) + f(x+1,y+1)]\}$$

$$\nabla S_y(x,y) = \{+[f(x-1,y-1)+2f(x,y-1)+f(x+1,y-1)] \\ +[f(x-1,y+1)+2f(x,y+1)+f(x+1,y+1)]\}$$

4. Energy of Laplacian of the image (EOL) [7]

$$EOL = \sum_x \sum_y (f_{xx} + f_{yy})^2$$

Where

$$f_{xx} + f_{yy} = -f(x-1,y-1) - 4f(x-1,y) - f(x-1,y+1) - \\ 4f(x,y-1) + 20f(x,y) - 4f(x,y+1) - f(x+1,y-1) - \\ 4f(x+1,y) - f(x+1,y+1)$$

5. Spatial frequency (SF) [7]

It is modified version of EOG.

$$SF = \sqrt{(RF)^2 + (CF)^2}$$

Where RF and CF are row and column frequency respectively and is defined as

$$RF = \sqrt{\frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=2}^{N} [f(x,y) - f(x,y-1)]^2}$$

$$CF = \sqrt{\frac{1}{M \times N} \sum_{x=2}^{M} \sum_{y=1}^{N} [f(x,y) - f(x-1,y)]^2}$$

6. Energy Of Morphology Gradient (EOMG) [4]

De's method given in [4] proposes EOMG. The calculation is as follows:

$$G_d(r,c) = d(r,c) - f(r,c)$$
$$G_e(r,c) = f(r,c) - e(r,c)$$

Where, f(r,c) is original image, and d(r,c) and e(r,c) are dilated and eroded image respectively. Gd and Ge will give edges of the image. The structuring element used for erosion and dilation is:

Drod1 = {(0,-1),(0,1),(0,0),(-1,0),(1,0)}.

And then,

$$G(r,c) = G_d(r,c) + G_e(r,c)$$
$$EOMG = \sum_r \sum_c (G(r,c))^2$$

In De's method, the multi-focus images are divided block wise recursively. If one of the blocks, in the block pair, is fully focused and the other is fully out of focus, then there is no need to divide the block pair. But if this is not the case, each block in the block pair will be divided until the above condition holds or the block size is less than the minimum size permissible. The simple illustration of division is as follows:

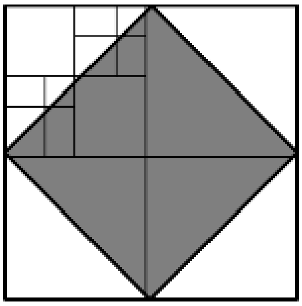


Fig. 2: Recursive subdivision of upper-left quadrant. Focus is on shaded regions [4]

To take decision about division, the rule given is, if Normalized Difference in Focus Measure (NDFM) is greater than the Threshold (T) then there is no need to divide the block pair further and the block with maximum focus measure is copied into the resultant image. The calculation of NDFM and T is as follows:

$$NDFM = \frac{Absolute\ difference\ in\ focus-measure}{sum\ of\ focus-measure}$$

$$M = \frac{Mean\ of\ NDFM\ at\ level\ 1}{NDFM\ at\ level\ 0} \times standard-deviation\ of\ NDFM\ at\ level\ 1 \times 100$$

$$T = M \times NDFM$$

PROPOSED METHOD

De's method in [4] will not work in following condition.

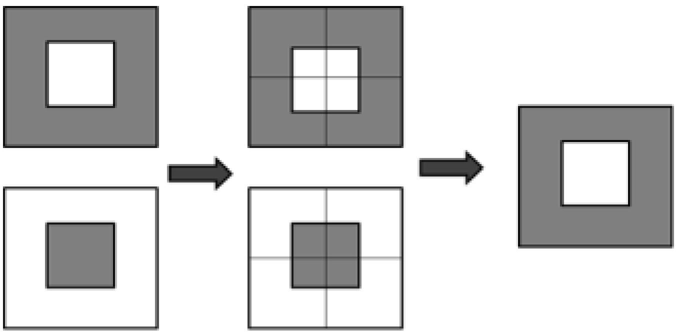


Fig 2.9: Case in which De's method will not work

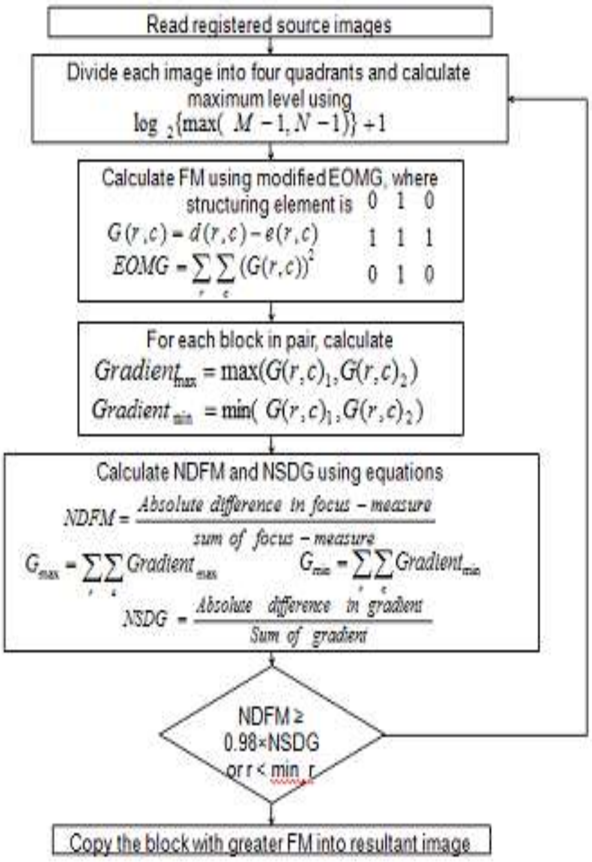
If the source images are centrosymmetric, the NDFM for corresponding blocks will be equal. And, the constant multiple M and threshold T will be zero. So, the blocks will not be subdivided further and the resulting image will be same as input image.

The quad-tree structure given in De's method [4] is optimized using Normalized Sum of Difference in Gradient (NSDG). In the block pair, if NDFM ≥ NSDG, then one block is fully focused and another block is fully out of focus. So, there is no need to further divide this block pair. Else, the block pair should be subdivided recursively. NSDG is normalized difference between maximum and minimum gradient. Maximum and minimum gradient maps approximate the image that is fully focused and fully out-of-focus. So, NDFM will be equal to NSDG only when one block is fully focused and another is fully out-of-focus in the block pair. But, image may have some noise. So, the constant 0.98 is multiplied to NSDG.

In [4], the level upto which decomposition takes place is calculated using minimum of size m and n. but if we calculate it using maximum from both, the image will be divided smaller parts and we can get better results.

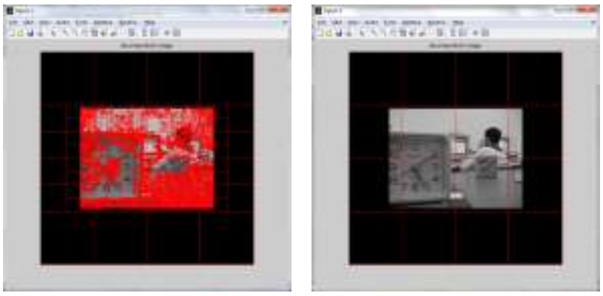
So in this work, efficient decomposition scheme, which uses NDFM and SMDG and more number of levels, is proposed.

FLOW CHART OF PROPOSED METHOD

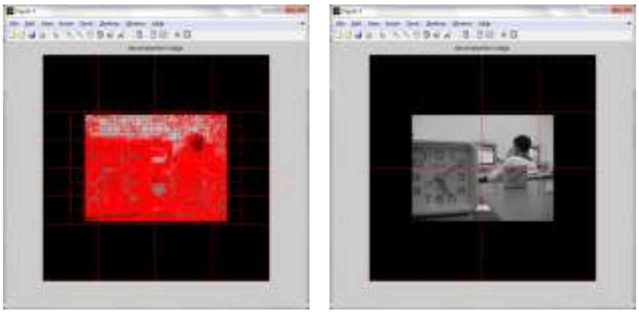


EXPERIMENTAL RESULTS

Input images_1:
Name: Lab
Size: 640 × 480



Proposed Method with EOMG VS De's Method with EOMG



Proposed Method with Variance vs De's Method with Variance

Reconstruction of the image

Proposed Method with EOMG vs De's Method with EOMG


Proposed Method with Variance vs De's Method with Variance

Time required (in second)

	De's Method		Proposed Method	
	Variance	EOMG	Variance	EOMG
Lab	1.262821	1.338480	2.144347	2.155020
Clock	0.512665	0.598573	0.594177	0.610862
Disk	1.143604	1.345117	2.153218	2.229368
OpenGL	1.525796	1.591069	2.419787	2.414968
Flower	1.318754	1.342539	2.132772	2.231808

Gradient similarity metric

	De's Method		Proposed Method	
	Variance	EOMG	Variance	EOMG
Lab	0.9998	0.9998	0.9997	0.9998
Clock	0.9988	0.9988	0.9987	0.9988
Disk	0.9996	0.9996	0.9994	0.9996
OpenGL	0.9997	0.9998	0.9996	0.9998
Flower	0.9991	0.9990	0.9991	0.9990

QP

	De's Method		Proposed Method	
	Variance	EOMG	Variance	EOMG
Lab	0.6912	0.7008	0.5067	0.7188
Clock	0.6206	0.6928	0.5497	0.6620
Disk	0.6453	0.6845	0.4699	0.6844
OpenGL	0.6602	0.7206	0.5864	0.7222
Flower	0.5455	0.5693	0.5575	0.5790

MSE

	De's Method		Proposed Method	
	Variance	EOMG	Variance	EOMG
Lab	63.4192	61.5229	137.2672	63.8140
Clock	997.8379	1.0505e+003	1.1861e+003	1.0394e+003
Disk	197.0200	166.8995	393.0137	166.3019
OpenGL	91.6588	40.8687	218.0674	40.4893
Flower	1.3151e+003	1.5918e+003	1.2437e+003	1.0992e+003

PSNR

	De's Method		Proposed Method	
	Variance	EOMG	Variance	EOMG
Lab	30.1086	30.2404	26.7551	30.0816
Clock	18.1402	17.9169	17.3897	17.9631
Disk	25.1857	25.9063	22.1867	25.9218
OpenGL	28.5091	32.0169	24.7449	32.0574
Flower	16.9412	16.1118	17.1836	17.7199

MI

	De's Method		Proposed Method	
	Variance	EOMG	Variance	EOMG
Lab	3.4754	3.5247	3.2625	3.5638
Clock	2.2744	2.1990	2.2702	2.1750
Disk	3.0702	3.2966	2.7020	3.2330
OpenGL	3.2774	3.5759	3.2101	3.5541
Flower	1.4956	1.1580	1.8262	1.0340

Entropy

	De's Method		Proposed Method	
	Variance	EOMG	Variance	EOMG
Lab	6.9368	6.9382	6.8798	7.0054
Clock	7.3381	7.3238	7.3691	7.3303
Disk	7.2694	7.2706	7.1662	7.3063
OpenGL	7.2532	7.2549	7.3396	7.2673
Flower	7.4927	7.4884	7.4190	7.3592

Conclusion

From the methods studied, I conclude that, De's method is based on the assumption that the energy distribution of an image is related to the energy distribution of its subregions. However, the energy distribution of an image is random, thus their decomposition method may not perform effectively in some cases. So, the quad tree needs to be optimized.

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