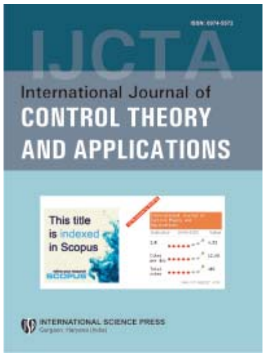

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Multi Focus Image Fusion with Top Hat Transform

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Abstract: In this paper, a novel image fusion with top hat transform is proposed. There are three main steps of proposed approach: initially the multi focus images are filtered using morphological filtering with top hat transform. This filter output is carried to acquire to acquire the rough segmentation result. The fusion process can make the decision based on rough segmented focused & defocused regions. The experimental results validate an effectiveness of the proposed method over standard DWT based on the multi focus image fusion. The quality of proposed method is verified with mutual information & quality factor. These measures prove the effectiveness of the proposed method.

Keywords: *Image fusion, Morphological operation, Top hat transform, Rough segmentation.*

1. INTRODUCTION

The Multi focus image fusion is the process of combining various focal length captured images in to single image. The importance of fusion process is viewing and analyzing single image is more convenient and efficient than a series of images. There is various multi focus image fusion algorithms are implemented in both spatial & transform domain [1]. The applications of image fusion are in office automation, industrial automation, biomedical, remote sensing, satellite communication etc. The basic fusion techniques are pixel selection, addition, subtraction or averaging. The most important used transform domain fusion methods are based on multi-scale transform.

The Examples of multi-scale algorithms include the discrete wavelet transform [2], gradient pyramid [3], dual tree complex wavelet transform [4], and so on.

Recently, advanced transform domain analysis methods, such as curve let transform [5], contour let transform [6–9], log-Gabor wavelet transform [10], and support value transform [11], retina-inspired model [12] and sparse representation [13] are also applied to image fusion.

In spatial domain pixels are directly involved in the fusion process. In few years, also various spatial domain fusion methods are proposed which can be divided into two categories: pixel based methods [14-16] and region based methods [17-20].

Recently, the advanced multi scale transforms are ridge lets and curve lets [4]–[7]. This approaches are very different from wavelet-like systems. The basic elements are Curve lets and ridge let's which exhibit very high directional sensitivity and are highly anisotropic. Therefore, by using curve let transform edges are represented better than wavelets, and it is well-suited for multi scale edge enhancement [7].

The rest of this paper is organized as follows. The morphological filtering is briefly explained in section 2, the proposed image fusion algorithm is described in section 3, the section 4, described experiment results and discussions. Finally, conclusion is given by section 5.

2. MORPHOLOGICAL FILTERING

Morphological filters are as increasing idempotent operators and their laws of composition are proved. The collection of non-linear operations related to the shape or morphology of features of an image is grouped in morphological image processing, such as boundaries,skeletons etc. one of the important analysis stages in image processing is Mathematical morphology. The mathematical tools of morphology are very useful for representation and description and content is based on set theory.

Dilation, erosion, opening and closing are the morphological operations. The morphological operations are performed on binary, gray scale and colour images.

The shape and size is different in morphological operation. This operation plays an important role in the structuring element. The Shape and size are defined by a number of 0s and 1s in the structuring elements.

Erosion and dilation are duals of each other with respect to set complementation and reflection. [Ref.21]

Opening means erosion operation followed by a dilation operation. The opening process can be mathematically represented as

$$A \circ B = (A \ominus B) \oplus B \tag{1}$$

Closing means dilation operation followed by a erosion operation. The closing process can be mathematically represented as

$$A \bullet B = (A \oplus B) \ominus B \tag{2}$$

Top-hat transform: There are two different types of top hat transform is white and black. The white top hat transform is defined as the difference between the input image and its opening by some structuring element. The black top-hat transform is defined dually as the difference between the closing and the input image. Various image processing tasks are used in top hat transform, like as feature extraction, background equalization, image enhancement and others.

Then, the white top-hat transform of f is given by :

$$T_w(f) = f - f \circ b \tag{3}$$

The black top-hat transform of f is given by :

$$T_b(f) = f \bullet b - f \tag{4}$$

3. PROPOSED METHOD

The Multi focus images are fused effectively with the proposed method. The morphological filtering of each source image is estimated by the focus information at the beginning. There are two different source image regions that are the definite focused region, and definite defocused region.

The proposed fusion algorithm consists of mainly three steps. First step is the given source images, second step is the morphological filtering and third step is the rough segmentation and finally fusion process.

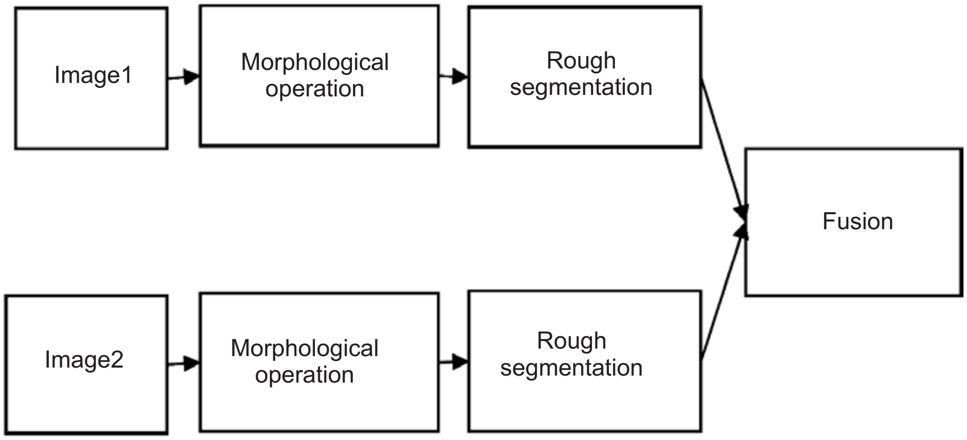

Figure 1: The block diagram of the proposed algorithm

Step1: The Multi focus images to be fused are considered [I_1, I_2]. The degradation of high frequency information is looks like unnatural image. In general focused and defocused regions are more important in high frequency information.

Step2: The high frequency information of source images are the input images are filtered with morphological filtering is measure. morphological filtering consists of two types of top-hat transforms:

$$d^n_0 = I_n - I_n \circ B \tag{5}$$

Where $n = 1, 2$

$$d^n_c = I_n \bullet B - I_n \tag{6}$$

Where B is structuring element (filtering image)

$$B = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

The filtered image is maximum value of the two transformed coefficients using equation 5-6 is given to the focus value of the corresponding pixel.

$$D_n(x, y) = \max\{d^n_0(x, y), d^n_c(x, y)\} \tag{7}$$

Step 3: The above filtered D_n images are follows the rough segmentation process. It segments into two regions with the use of filtered image, *i.e.*, the following equations using the definite focused region, and definite defocused region.

$$R_n(x, y) = \begin{cases} 1 & D_n(x,y) > D_{n+1}(x, y) \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

$$R_{n+1}(x, y) = \begin{cases} 1 & D_{n+1}(x,y) > D_n(x,y) \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

The resulting segmented image where $R_n(x, y) = 1$ or 0 and $R_{n+1}(x, y) = 1$ or 0 means that the point (x, y) of the source image in is in focus or out of focus respectively.

Step4: The final fused image is resolves based on the values of the above rough segmented regions *i.e.*:

$$\mathrm{I_F}(x, y) = \begin{cases} \mathrm{I}_n(x,y) & \text{if} \quad \mathrm{R}_n(x,y)=1 \\ \mathrm{I}_{n+1}(x,y) & \text{elseif} \quad \mathrm{R}_{n+1}(x,y)=1 \\ \dfrac{\mathrm{I}_n(x,y)+\mathrm{I}_{n+1}(x,y)}{2} & \text{otherwise} \end{cases} \tag{10}$$

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4. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed method executed with MATLAB 7.8.0software. The efficiency of proposed method is verified with various focal variant images. In morphological stage top-hat transform structuring element B is used. The fused images with proposed method are shown in the following figure. The figure shows top-hat morphological output, Rough segmentation output and final fused image. The quality of proposed method is verified with mutual information, quality factor and the results are tabulated in table-1.Standard DWT based fusion method is compared with the proposed method.

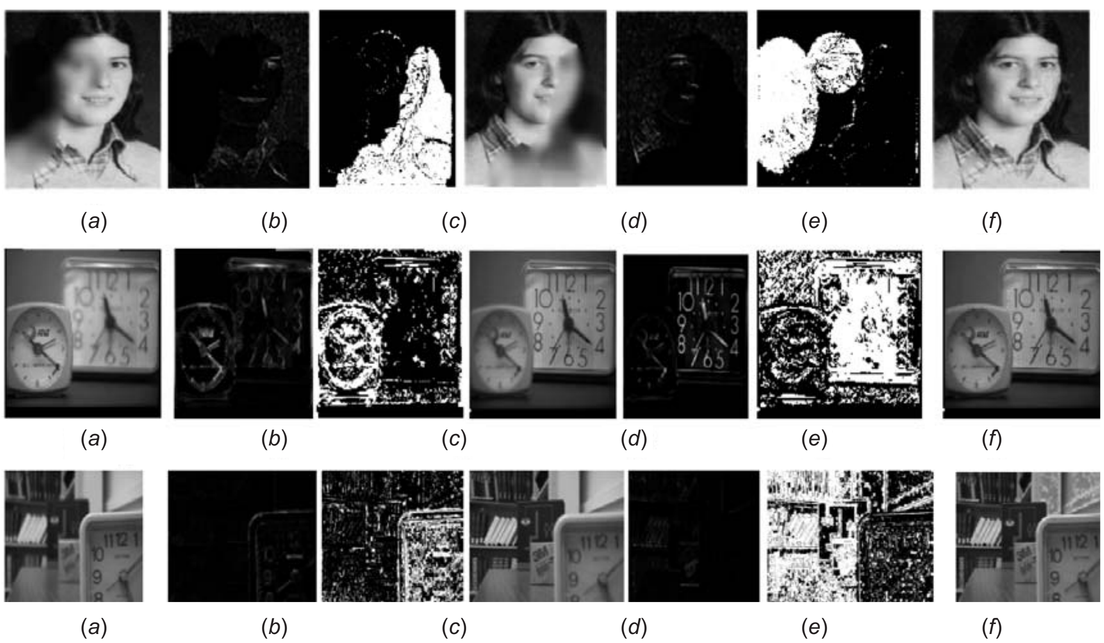
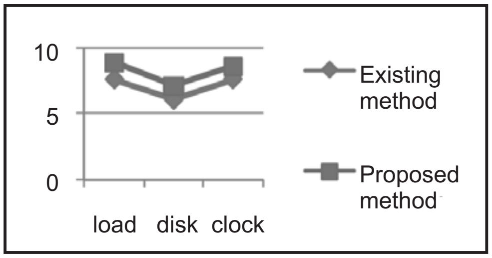


Figure 2: (*a*), (*d*): input images-$\mathrm{I}_1, \mathrm{I}_2$; (*b*), (*e*): morphological filter output-D_n, D_{n+1}; (*c*), (*f*): rough segmentation output R_n, R_{n+1}; (*g*): final fused image I_f.

Table 1
The Fusion methods performance measures based on PSNR

Images	*Existing method*		*Proposed Method*	
	Mutual Information	*QAB/F*	*Mutual Information*	*QAB/F*
Load	7.6779	0.5882	8.9463	0.8118
Disk	6.1514	0.5944	7.1591	0.6374
Clock	7.6922	0.5340	8.6352	0.7716



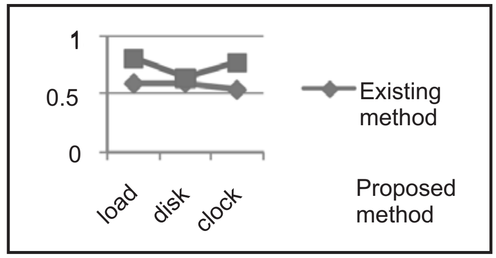


Figure 3: Graphical Representation of various performance measures: (*a*) Mutual Information, (*b*) $Q^{AB/F}$

4.1. Mutual Information

Mutual information defines the mutual dependence of two two input images. Here, MI measures the information that reference and the fused image share:

$$MI_{RF} = \sum_{i=1}^{L}\sum_{j=1}^{L} P_{RF}(i, j)\log_2 \frac{P_{RF}(i, j)}{P_R(i)\, P_F(j)} \tag{11}$$

Where P_{RF} is the normalized joint gray level histogram of images Reference image (R) and Fused image (F), P_R and P_F are the normalized marginal histograms of the two images.

4.2. Quality factor ($Q^{AB/F}$)

The metric $Q^{AB/F}$ is defined as follows:

$$Q^{AB/F} = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M}\left(Q^{AF}(n,m)W^{A}(n,m) + Q^{BF}(n,m)W^{B}(n,m)\right)}{\sum_{n=1}^{N}\sum_{m=1}^{M}\left(W^{A}(n,m) + W^{B}(n,m)\right)} \tag{12}$$

Where $Q^{AF}(n, m) = Q^{AF}_{g}(n, m)\, Q^{AF}_{\alpha}(n, m)$; $Q^{AF}_{g}(n, m)$ and $Q^{AF}_{\alpha}(n, m)$ are the edge strength and orientation preservation values, respectively; $^{n, m}$ represents the image location; and $^{N, M}$ are the size of images, respectively. $Q^{BF}(n, m)$ is similar to $Q^{AF}(n, m)$. $W^{A}(n, m)$ And $W^{B}(n, m)$ reflect the importance of $Q^{AF}(n, m)$ and $Q^{BF}(n, m)$, respectively.

5. CONCLUSION

This proposed method evolved the fusion of multi focus images using top hat transform. In the proposed method morphological processing and rough segmentation plays an essential role to isolate focus and defocused region. These isolated regions are managed to produce final fused image. Unlike standard DWT fusion methods, the proposed method managed well with the focus and defocused regions of input images to generate fused image. The efficiency of proposed method proved in term of visual perception and performance measures of MI & Q. in the future, it can further investigate the with other related images fusion methods.

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