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An Algorithm to Perform Fusion of Partially Focused Images in Fuzzy Domain

Meenu Manchanda
Vaish College of Engineering, Rohtak, Haryana, India

Abstract: -- **An algorithm for fusion of partially focused input images in fuzzy domain is proposed. Since fuzzy transform possesses important properties such as shift-invariance, ability to preserve edges in an image, ability to provide better approximation etc. and therefore has been preferred in the paper. Since important features in an image are generally larger than one pixel and therefore the proposed algorithm uses fusion rule based on more than one coefficient (i.e. window based fusion rule) to fuse input images in the fuzzy transform domain. Experiments show that the proposed algorithm is effective and the results are acceptable.**

Keywords— Image fusion, fuzzy transform, evaluation metrics.

1. INTRODUCTION

Because of limited depth-of-focus of commonly used optical lenses, only the objects that lie within a certain range of distance appear sharp whereas all other objects tend to be blurred. this is undesirable for accurate interpretation and analysis of images. image fusion [1] offers a promising solution to this problem by combining multiple partially focused images of the same scene into a single image that has all the objects well in-focus. it has been proven to be an efficient way to increase the depth-of-focus of image capturing devices in a wide variety of applications such as computer vision, microscopic imaging, digital imaging etc.
A great variety of image fusion algorithms to fuse partially focused images have been proposed in literature. The simplest way [2] to perform fusion is to take pixel-by-pixel, weighted average of input images. However, this often results in contrast reduction. To improve the quality of fused image, multiscale analysis tools such as pyramid transforms and wavelet transforms [3, 4] are used for the purpose of image fusion. However, it is proved that pyramid-based algorithms produce blocking effects in fused images whereas wavelet based algorithms capture limited directional information and has poor performance at edges and textured regions. These issues are solved with the development of multiscale geometric tools such as contourlet, shearlet and their non-subsampled versions.

In recent years, several researchers have proposed image fusion algorithms based on fuzzy logic. Manchanda et. al. proposed image fusion algorithm based on fuzzy transform [5,6]. Fuzzy transform converts a set of two dimensional functions in one space onto finite dimensional matrices in another space. The main advantage of using fuzzy transform is that it is shift-invariant and has the capability of preserving edges in an image. Thus, an algorithm to perform fusion of partially focused images in fuzzy domain is proposed in the paper.
The remaining paper is organized as follows: Section II discusses fuzzy transform, Section III presents the proposed algorithm, results are illustrated and discussed in Section IV and conclusion is drawn in Section V.

2. FUZZY TRANSFORM

Fuzzy transform converts an original function into a finite (say N) dimensional vector. The inverse- fuzzy transform (Inv-fuzzy transform) converts back the finite dimensional vector into original function producing either the original function or a function that approximates the original function in such a manner that universal convergence is achieved. Fuzzy transform possesses various important properties such as ability to provide better approximation, shift invariance, ability of preserving edges, smoothing, capabilities of removing noise, etc. and therefore has been successfully used in image fusion.

The fuzzy transform [7] is defined as:

$$F(i,j) = \frac{\sum_{k=1}^{M}\sum_{l=1}^{N} f(x_k, y_l) A_i(x_k) B_j(y_l)}{\sum_{k=1}^{M}\sum_{l=1}^{N} A_i(x_k) B_j(y_l)}$$

where $x_k, y_l \in I$, $k = 1,2,\ldots,M$ and $l = 1,2,\ldots,N$ are given two-dimensional data points $(M, N \geq 1)$ such that for each $k \in 1,2,\ldots,M$ there exists $i \in 1,2,\ldots,m$ with fuzzy partitions $A_i(x_k) > 0$ and for each $l \in 1,2,\ldots,N$ there exists $j \in 1,2,...,n$ with fuzzy partitions $B_j(y_l) > 0$. An example of a two dimensional triangular fuzzy partitions is shown in Figure. 1. $F(i, j)$ in Equation (1) exhibits local information about the original function and are called the fuzzy transform coefficients. The Inv- fuzzy transform is defined as [1]:

$$\hat{f}(x_k, y_l) = \sum_{i=1}^{m}\sum_{j=1}^{n} F(i, j) A_i(x_k) B_j(y_l)$$

for $k = 1,2,..., M$ and $l \in 1,2,..., N$.

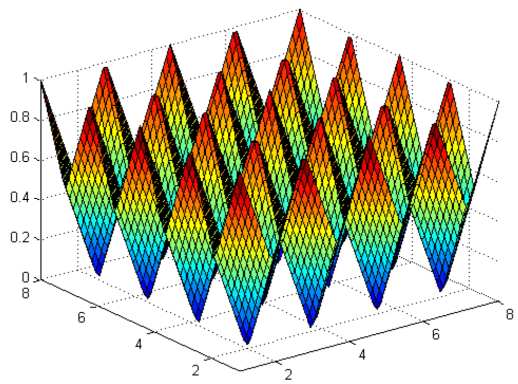

Figure 1: An example of a two dimensional triangular fuzzy partitions

The advantages of fuzzy transform are as follows:

1. It is powerful transformation technique that is capable of preserving features in an image.
2. It deals with vectors and matrices, therefore has low computational complexity.
3. It is shift invariant.
4. It is invariant with respect to interpolating and least square approximation of input function.
5. It possesses noise removing abilities as well as smoothing abilities.
6. It has the capability of preserving monotonicity and Lipschitz continuity of an image. This helps in improving the quality of reconstructed image.

3. THE PROPOSED ALGORITHM

In order to fuse partially-focused input images, the proposed method initially divides both input images into non-overlapping blocks of size 8×8. These blocks are then mapped into 7×7 fuzzy transform coefficients using Equation (1). These fuzzy transform coefficients are then combined based on a fusion rule. The fused fuzzy transform coefficients are then mapped back into 8×8 size of blocks using Inv-fuzzy transform. The fused image, Z is further reconstructed using these fused blocks.

The fusion rules aim to select the coefficient from either of the input image that has utmost importance for producing the final fused image. The various fusion rules differ in the way the coefficients are chosen for producing the final fused image. Three of the popularly used fusion rules are explained as follows:

1. Averaging (AG) based fusion rule: In AG based fusion rule, average of fuzzy transform coefficients of both input images is used to produce the respective fuzzy transform coefficients of the fused image. Mathematically,

$$F_Z(i, j) = F_X(i, j) + F_Y(i, j)$$

where F_X, F_Y and F_Z represents fuzzy transform coefficients of images X, Y and Z respectively

2. Select maxima (SM) coefficient based fusion rule: In SM based fusion rule, the fuzzy transform coefficient which has maximum value from either of the input images is used to produce the final fused image i.e the coefficient from either of the input image is retained depending on which coefficient has higher value. Mathematically,

$$F_Z(i, j) = \max[F_X(i, j), F_Y(i, j)]$$

3. Window (WD) based fusion rule: Since important features in an image are generally larger than one pixel, therefore the selection of fuzzy transform coefficient i.e. fusion rule must also be applied on more than one coefficient at a time [3].

Proposed WD based fusion rule: The flowchart of the proposed algorithm is shown in Figure.2. Importance (I) of a coefficient is determined as the energy over an m×m (generally 3×3) window over it i.e.

$$I^{F_X}(i, j) = \sum_{k=-m}^{m}\sum_{l=-m}^{m} F_X(i+k, j+l)^2$$

$$I^{F_Y}(i, j) = \sum_{k=-m}^{m}\sum_{l=-m}^{m} F_Y(i+k, j+l)^2$$

After measuring the importance of each coefficient in both the images, the fuzzy transform coefficients are fused using either `averaging' or `selection' based rule depending on a matching index between them. The matching index, M, between two coefficients from images X and Y around the same neighborhood is calculated as:

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$$M(i,j)=\frac{\sum_{k,l}F_X(i+k,j+l)F_Y(i+k,j+l}{0.5(I^{F_x}(i,j)+I^{F_Y}(i,j))})$$

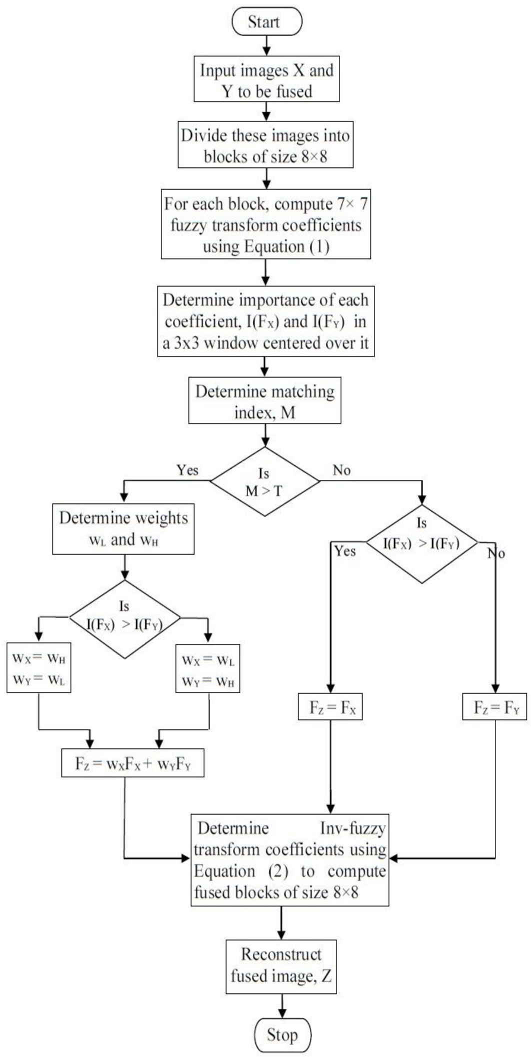


Figure 2: Flowchart for the proposed algorithm

Matching index indicates the similarity of two images at a particular pixel location. If M=1, then the two images are very similar locally; whereas M= -1 indicates quite different images. Depending on the matching measure, fusion takes place as follows:

(i) If M >T, fuzzy transform coefficients are combined through weighted average based fusion rule i.e.

$$F_Z(i,j)=w_x(i,j)F_X(i,j)+w_Y(i,j)F_Y(i,j)$$

where the weights are calculated as follows based on matching index and threshold, T

$$w_L=\frac{1}{2}\left[1-\frac{1-M}{1-T}\right]$$

$$w_H=\frac{1}{2}\left[1+\frac{1-M}{1-T}\right]$$

Higher weight is assigned to the coefficient with higher energy in the neighborhood whereas lower weight is assigned to the other coefficient i.e.

If $I^{F_X}(i,j)>I^{F_Y}(i,j)$, then

$w_x=w_H$ and $w_Y=w_L$

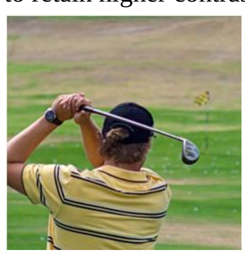
If $I^{F_X}(i,j)\le I^{F_Y}(i,j)$, then

$w_x=w_L$ and $w_Y=w_H$

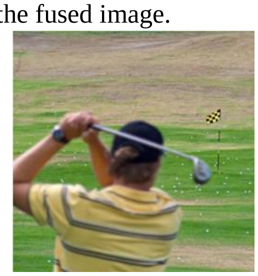
(ii) If M < T, then the fuzzy transform coefficients with higher energy is selected i.e.

$$F_Z(i,j)=\begin{cases}F_X(i,j),\ if\ I^{F_X}(i,j)>I^{F_Y}(i,j)\\ F_Y(i,j),\ if\ I^{F_X}(i,j)\le I^{F_Y}(i,j)\end{cases}$$

The concept behind selecting the coefficients with higher importance when matching index is below a certain threshold is to retain higher contrast in the fused image.



(a) Input Image (X)



(b) Input Image (Y)

(c) Fused Image (Z)

Figure 3: Subjective image quality assessment of Set 1 partially focused images

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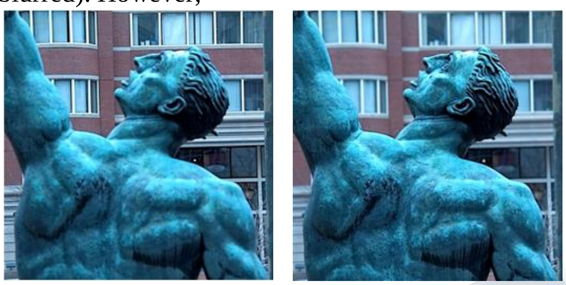
4. RESULTS AND DISCUSSION

Fusion of multifocus images with AG, SM and proposed fusion rule in fuzzy transform domain has been experimented on four sets of multifocus images. These images are available on "Lytro Multifocus Image Dataset". These sets of partially-focused input images are shown in Figure. 3(a,b), Figure. 4(a,b), Figure. 5(a,b) and Figure. 6(a,b). In these figures, images shown in Figure. 3(a) - Figure. 6(a) have foreground objects `in-focus' (i.e. clear) and background `out-of-focus' (i.e. blurred). However,



(a) Input Image (X) *(b) Input Image (Y)*

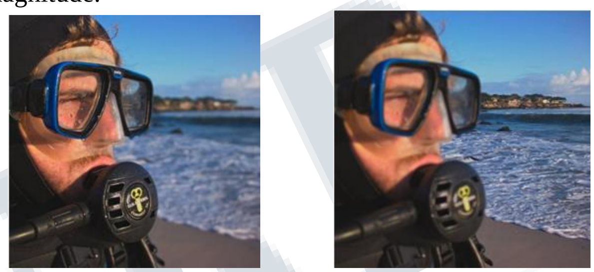
(c) Fused Image (Z)

Figure 4: Subjective image quality assessment of Set 2 partially focused images

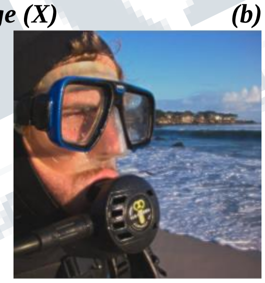
images shown in Figure. 3(b) - Figure. 6(b) have foreground objects `out- of-focus' and background `in-focus'. The ideal 'all-in-focus' fused image is the one that is best focused everywhere. The fused images for these pairs of input images are shown in Figure. 3(c), Figure. 4(c), Figure. 5(c) and Figure. 6(c) respectively. From the visual results, it is found that the proposed fusion rule in fuzzy transform domain successfully combines partially-focused images into an 'all-in-one' well focused fused image.

To prove the effectiveness of the proposed fusion rule in comparison to the popularly used fusion rules i.e. AG and SM, seven image quality evaluation metrics are used for objective comparison. These metrics are [8]:

- Feature mutual information (FMI) that determines the amount of image features transferred from input images into the fused image.
- Structural similarity index measure (SSIM) that takes into consideration the characteristics of human visual system to determine the structural similarity between input images and the fused image.
- Feature similarity index measure (FSIM) that determines the similarity between input images and the fused image based on the combination of phase congruency and gradient magnitude.



(a) Input Image (X) *(b) Input Image (Y)*



(c) Fused Image (Z)

Figure 5: Subjective image quality assessment of Set 3 partially focused images

- Edge strength (Q) that measures the amount of edge information that has been transferred from input images into the fused image.
- Fusion loss (FL) that determines the amount of information that has been lost (if any) during the fusion process.
- Fusion artifacts (FA) that measures the amount of undesirable artifacts that has been introduced (if any) during the fusion process.

(a) Input Image (X) *(b) Input Image (Y)*

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(c) Fused Image (Z)

Figure 6: Subjective image quality assessment of Set 4 partially focused images

• Spatial frequency (SF) refers to the amount of details present in a stimulus per degree of visual angle. An image with small details and sharp edges has high spatial frequency whereas an image with coarser information has low spatial frequency.

Table 1: Comparison of objective metrics obtained using different fusion rules in fuzzy transform domain for Set 1 partially focused images

Metrics	AG	SM	WD
FMI	0.9167	0.9353	**0.9370**
SSIM	0.7578	0.8932	**0.8944**
FSIM	0.8395	0.9217	**0.9226**
Q	0.6855	0.9299	**0.9368**
FL	0.2224	0.0681	**0.0622**
FA	0.0919	0.0018	**0.0008**
SF	4.6999	4.7040	**4.8732**

Higher values of FMI, SSIM, FSIM and Q whereas lower values of FL and FA indicates better fusion results. It is also noted that the total fusion performance Q, FL and FA are complimentary i.e. the sum of these metrics is unity. Table 1-Table 4 shows the comparison of these objective parameters obtained using AG, SM and proposed fusion rule in fuzzy transform domain. From these objective results, it is observed that maximum of the objective parameters obtained using fuzzy transform based fusion algorithm with the proposed rule have attained their best values. Thus, it is concluded that to take into account the important features contained in an

Table 2: Comparison of objective metrics obtained using different fusion rules in fuzzy transform domain for Set 2 partially focused images

Metrics	AG	SM	WD
FMI	0.9160	0.9304	**0.9309**
SSIM	0.7010	0.8119	**0.8124**
FSIM	0.8110	0.8772	**0.8777**
Q	0.5634	0.8135	**0.8214**
FL	0.3700	0.1832	**0.1774**
FA	0.0665	0.0032	**0.0011**
SF	4.7595	4.7615	**4.9406**

Table 3: Comparison of objective metrics obtained using different fusion rules in fuzzy transform domain for Set 3 partially focused images

Metrics	AG	SM	WD
FMI	0.9281	0.9623	**0.9309**
SSIM	0.7449	0.9257	**0.9310**
FSIM	0.8258	0.9499	**0.9530**
Q	0.5732	0.9408	**0.9586**
FL	0.3822	0.0580	**0.0408**
FA	0.0446	0.0012	**0.0005**
SF	7.2227	7.6414	**8.0841**

Table 4: Comparison of objective metrics obtained using different fusion rules in fuzzy transform domain for Set 4 partially focused images

Metrics	AG	SM	WD
FMI	0.9258	0.9439	**0.9451**
SSIM	0.6858	0.8528	**0.8535**
FSIM	0.7679	0.8875	**0.8880**
Q	0.5662	0.8162	**0.8416**
FL	0.3823	0.1824	**0.1580**
FA	0.0514	0.0013	**0.0003**
SF	4.9987	4.9884	**5.2029**

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image, fusion rule should be applied on more than one coefficient.

5. CONCLUSION

An algorithm that performs fusion of partially focused images into a single all-in-one focused image is proposed. The proposed algorithm initially divides input images into blocks of same size that are mapped into fuzzy transform coefficients. The resultant fuzzy transform coefficients are then fused using proposed window-based fusion rule to produce the fused image. The objective fusion results obtained using the proposed fusion rule in fuzzy transform domain are compared with the objective results of the AG and SM based fusion rule in fuzzy transform domain. From these results it is concluded that fusion rule when applied on more than one coefficient produces better fusion results. Visual results show that the proposed algorithm produces fused images with all the objects well `in-focus'.

REFERENCES

[1] Meenu Manchanda and Rajiv Sharma, “Fuzzy transform-based fusion of multiple images”, International Journal of Image and Graphics, vol. 17, no. 2, 1750008, 2017.

[2] Q. Zhang and B. L. Guo, “Multifocus image fusion using the non- subsampled contourlet transform”, Signal Processing, vol. 89, no. 7, pp. 1334–1346, 2009.

[3] Shutao Li, James T Kwok, and Yaonan Wang, “Multifocus image fusion using artificial neural networks”, Pattern Recognition Letters, vol . 23, no. 8, pp.985– 997, 2002.

[4] Zheng Liu and Robert Lagani`ere. Phase congruence measurement for image similarity assessment. Pattern Recognition Letters, vol. 28, no. 1, pp. 166– 172, 2007.

[5] Meenu Manchanda and Rajiv Sharma, “A novel method of multimodal medical image fusion using fuzzy transform” Journal of Visual Communication and Image Representation, vol. 40, pp. 197–217, 2016.

[6] Meenu Manchanda and Rajiv Sharma, “Fuzzy transform-based fusion of multiple images”, International Journal of Image and Graphics, vol. 17, no. 2, pp. 1750008, 2017.

[7] Alfred Mertins, ‘Multifocus image fusion by combining curvelet and wavelet transform”, Optical Engineering, vol. 38, no 6, pp. 991–1000, 1999.

[8] Mark JL Orr et al., “Introduction to radial basis function networks”, 1996.

