Multi-focus Image Fusion Using Stationary Wavelet Transform (SWT) with Principal Component Analysis (PCA)

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Abstract

Multi-focus image fusion creates meaningful image from two or more meaningless images which have same scenes with meaningful image. These images have different focus points. The image after proposed method is named as all-in-focus image. This image has more information from source images. Multi-focus image fusion is that combining two or more source images which have same scenes but different focuses. In this paper, we proposed lifting wavelet transform based hybrid technique. Principal Component Analysis is used as a fusion rule. Firstly, source images are decomposed using Lifting Wavelet Transform. After this, all source images divided into four sub-bands. Secondly, the each sub-band of source images is applied Prinicipal Component Anlaysis. And eigenvectors and eigenvalues are calculated. Calculated eigenvectors are used to fuse sub-bands. Finaly, the new sub-bands are created and Inverse Lifting Wavelet Transform is implemented for new sub-bands. The fused image is created and to perform quality Mutual Information,Petrovics metric and Average Gradient are calculated. The results show that the new hybrid technique is successful for multi-focus image fusion. All in focus image is more informative so it can be processed easily. Multi-focus image fusion is used different areas such as; health system, wsn, etc. We proposed a new hybrid method using Stationary Wavelet Transform (SWT) with Principal Component Analysis (PCA). This method uses transform domain. We used SWT for feature extraction. SWT decompose image four different sub-bands. After extraction feature, to combine images we proposed PCA based fusion rule. With PCA from sub-bands of source images are computed eigenvectors and selected maximum eigenvector of these sub-bands because maximum eigenvector represents image ideally. After application fusion rule, we got four new sub-bands and reconstructed new all in focus image using this sub-bands with inverse SWT. Mutual Information, Standard Deviation, Spatial Frequency and Petrovic's Metric are used as quality metrics.

1. Introduction

In CCD devices owing to the constrained deepness-of-focus of lenses, getting an image that includes all suitable objects 'in focus' is generally not possible. Multi-focus image fusion is used to overcome this problem. Multi-focus image fusion is that two or more images with different focuses are converted to all in focus single image. After the fusion, all important information of source images should be transmitted into the all-in-focus image with no introduction of artifacts. And, the fusion method must be dependable and resistant to noises [1–3].

The average method which gets pixel-by-pixel average of the source images is the simplest multi-focus image fusion method. However, using this method generally causes to un-wanted effects such as decreasing contrast. In last years, different alternative methods are proposed using multi-scale transforms. These methods firstly decompose input images, and process the decomposition levels using different ways. Finally, an inverse wavelet transform is implemented to get last fused image. The Laplacian pyramid was implemented by Burt and Andelson. Moreover, the discrete wavelet transform (DWT) (Chipman et al., 1995; Koren et al., 1995; Li et al., 1995; Yocky, 1995, 1999) has also been proposed. Providing directional information is one of the advantages of wavelets looking to pyramids. The other one, the wavelet-based methods can be chosen to be orthogonal, according to the pyramid-based methods, DWT carries optimal information across with different resolutions. [2].

Spatial Fusion and Transform fusion are two approaches for image fusion. We use the pixel value of image not transform pixels any domain. The pixel values are evaluated to fuse image. Simple averaging, simple max etc. are examples of these methods. Transform domain fusion methods use pyramid or Wavelet Transform (WT). DWT is the most widely used transform for image fusion since it decreases structural distortions. But, DWT has disadvantages such as deficiency of shift invariance and poor directionality, to overcome these disadvantages, Stationary Wavelet Transform (SWT) is implemented. Other disadvantage of The Discrete Wavelet Transform is not a time- invariant transform. SWT which is called un-decimated DWT, is applied to overcome the translation-invariance problem. In place of up-sampling the filters by inserting zeros between the filter coefficients; SWT suppresses the down-sampling step of the decimated algorithm. "à trous", means that algorithms in which the filter is up-sampled. As with the decimated algorithm, firstly the filter is implemented to rows and then to columns [4].

We implemented a hybrid method using SWT and Principal Component Analysis (PCA). SWT is a transform domain technique, we use SWT decompose image four sub-bands and PCA is used for combining pixel values using fusion rules. The results show that SWT and PCA are successful in multi-focus image fusion area.

The paper is organized as follow: Stationary Wavelet Transform is illuminated in Section 2. Section 3 includes image fusion using Principal Component Analysis. Applied method is illuminated in Section 4. Section 5 includes Quality Metrics. Section 6 and Section 7 respectively describe experimental results and conclusions.

2. Stationary Wavelet Transform

Discrete wavelet transform has two disadvantages time-variant and poor directionality. To overcome these, we can use Stationary Wavelet Transform (SWT). These algorithms are implemented firstly on rows and then to columns. After implementing SWT, four images are created. Three of them are detail coefficients and one of them is approximation coefficients. These four images are same size with source images but their resolution is half of the original images. The decomposition of image in SWT domain is as shown in Fig. 1.

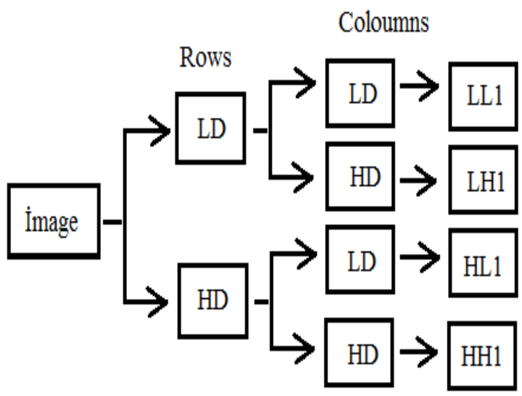


Fig. 1. Decomposition flow diagram of SWT

3. Image Fusion Using Principal Component Analysis

Principal Component Analysis (PCA) is a tool that converts correlated variables to uncorrelated ones. Image compression and classification are two main areas of PCA. The PCA includes a mathematical processing that converts correlated variables to uncorrelated variables called principal components. PCA extracts optimum features of the data set. The first principal component calculates the data with maximum variance. First principal component with the maximum variance is received to be throughout the direction. The second one is limited in the horizontal of sub-space. In this Subspace, the direction of maximum variance is pointed from this component [5].

The source images S1 and S2 are decomposed four sub-bands with SWT.LL1, LH1, HL1, HH1 are sub-bands for S1 image. LL2, LH2, HL2, HH2 are sub-bands for S2 image. For these sub-bands PCA has been calculated and maximum eigenvectors are selected. Then to combine source sub-bands, each sub-band is multiplied and summed. After this processing a new sub-band which belongs to fused image is created. Sub-bands of fused image are LL, HL, LH, HH that are calculated using Eq. 1., Eq. 2., Eq. 3. and Eq. 4., respectively [6].

$$LL=p1*LL1+p2*LL2 \tag{1}$$
$$HL=p3*HL1+p4*HL2 \tag{2}$$
$$LH=p5*LH1+p6*LH2 \tag{3}$$
$$HH=p7*HL1+p8*HL2 \tag{4}$$

P1 is maximum eigenvector for LL1 sub-band, p2 is maximum eigenvector for LL2 sub-band. Other p values are calculated like p1 and p2.

4. Proposed Method

We proposed a hybrid technique for multi-focus image fusion using SWT with PCA. SWT is preferred due to shift invariant. Source images are decomposed using SWT and PCA is used fusion rule to combine source images. Proposed method will be told step by step below;

a) Two or more images with M*N size are converted to grayscale image.

b) These images are decomposed using SWT. After implementing SWT, each image is transformed four sub-bands same size with original images.

c) LL1, LH1, HL1, HH1 are sub-bands for first image. LL1 is approximation coefficients and others are detail coefficients for first image. LL2, LH2, HL2, HH2 are sub-bands for second image.

d) PCA is applied sub-bands of the original images. Using PCA eigenvectors and eigenvalues are calculated for each sub-band.

e) After calculating maximum eigenvector of each sub-band is selected. maximum eigenvector represents the data ideally.

f) For sub-bands a new fused sub-band is calculated pixel by pixel using Eq. 1., Eq. 2., Eq. 3. and Eq. 4. LL, HL, LH, HH are sub-bands for fused image.

g) To reconstruct image using LL, LH, HL, HH sub-bands is used ISWT. After implementing this, all in focus image is created and showed.

h) Finally, quality of algorithm is calculated using quality metrics without reference image such as standard deviation, spatial frequency and mutual information. Flow diagram of algorithm is shown Fig. 2.

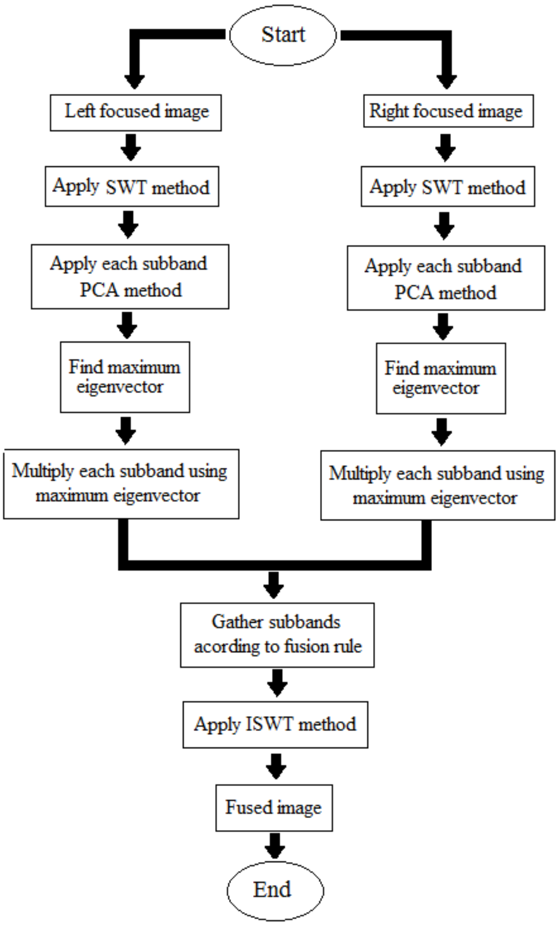


Fig. 2. Flow diagram of proposed method

5. Quality Metrics

Spatial frequency (SF): In the fused image, spatial domain frequency includes the activity level. It is represented by Eq. 5. [7].

$$SF = \sqrt{RF^2 + CF^2} \tag{5}$$

Where,

$$CF = \frac{1}{M*N}\sqrt{\sum_{x=1}^{M}\sum_{y=2}^{N}(I_f(x,y) - I_f(x,y-1))^2} \tag{6}$$

$$RF = \frac{1}{M*N}\sqrt{\sum_{x=1}^{M}\sum_{y=2}^{N}(I_f(x,y) - I_f(x-1,y))^2} \tag{7}$$

Where, $I_f(x,y)$ is intensity of fused image, the height and width of fused image are M and N respectively. When SF has larger value, fused image includes more detail and fusion performance is better.

Standard Deviation (SD): SD is combining of the signal and noise parts. When the noise is lower, this metric is more efficient. SD shows the contrast of the fused image. If an image has high contrast; also its standard deviation will be high. It is represented by Eq. 8. [7].

$$SD = \sqrt{\sum_{x=0}^{L}(i - i')^2 * h_{I_f}(x)} \tag{8}$$

Where, the normalized histogram is shown with $h_{I_f}(x,y)$ and the number of frequency levels is shown with L.

Fusion Mutual Information (FMI): The dependence degree of the images is measured with MI. If MI has large value, Quality will be high. It is represented by Eq. 9. [7].

$$\boldsymbol{FMI} = MI_{I_{1I_F}} + MI_{I_{2I_F}} \tag{9}$$

Where,

$$MI_{I_{1I_F}} = \sum_{x=1}^{M}\sum_{y=1}^{N} h_{I_{1I_f}}(x,y) * \log_2 \frac{h_{I_{1I_f}}(x,y)}{h_{I_1}(x,y) * h_{I_2}(x,y)} \tag{10}$$

$$MI_{I_{2I_F}} = \sum_{x=1}^{M}\sum_{y=1}^{N} h_{I_{2I_f}}(x,y) * \log_2 \frac{h_{I_{2I_f}}(x,y)}{h_{I_1}(x,y) * h_{I_2}(x,y)} \tag{11}$$

Joint histogram between $I_1(x,y)$ and, $I_f(x,y)$,is shown as $h_{I_{1I_f}}(x,y)$, $I_f(x,y)$ and $I_2(x,y)$ is shown as $h_{I_{2I_f}}(x,y)$. The mutual information of fused image is shown with FMI.

Petrovic's Metric (QAB/F): The metric calculates the edge information which is delivered source images to fused image. It is represented by Eq. 12. [8].

$$Q^{AB/F} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(Q^{AF}(i,j)w^A(i,j) + Q^{BF}(i,j)w^B(i,j))}{\sum_{i=1}^{M}\sum_{j=1}^{N}(w^A(i,j) + w^B(i,j))} \tag{12}$$

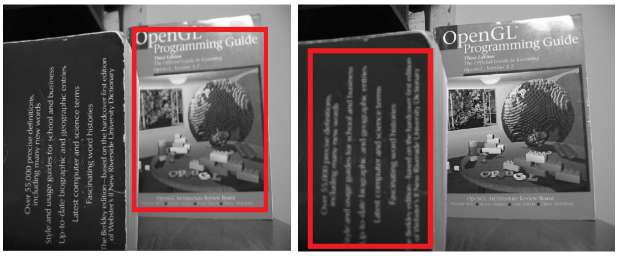
Where,

$$Q^{AF}(i,j) = Q_a^{AF}(i,j)Q_b^{AF}(i,j) \tag{13}$$

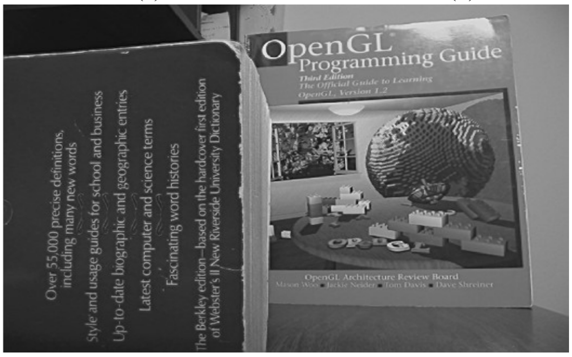
$Q_a^{AF}(i,j)$ and $Q_b^{AF}(i,j)$ are the perceptual loss of information. $w^A(i,j)$ and $w^B(i,j)$ are the weights of $Q^{AF}(i,j)$ and $Q^{BF}(i,j)$ respectively. Relation between source image A and fused image is represented as $Q_a^{AF}(i,j)$ and the edge information of A is shown with $w^A(i,j)$. When the QAB/F id bigger, the delivered edge and structure information of source images are bigger.

6. Experimental Results

The tests of this hybrid method are done with different images (color and grayscale). The images are popular images in literature. Some of the images are displayed in Fig. 3., Fig. 4., Fig. 5. and Fig. 6. These are book, flower, desk and lytro image respectively. Left focused images are represented by (a), right focused images are represented by (b) and all- in-focused images are represented by (c). Also, non-focused areas of source images are shown with red box in (a) and (b).

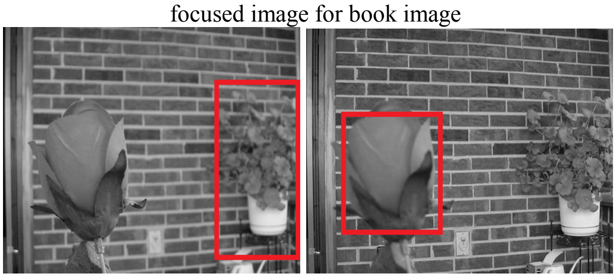


(a) (b)

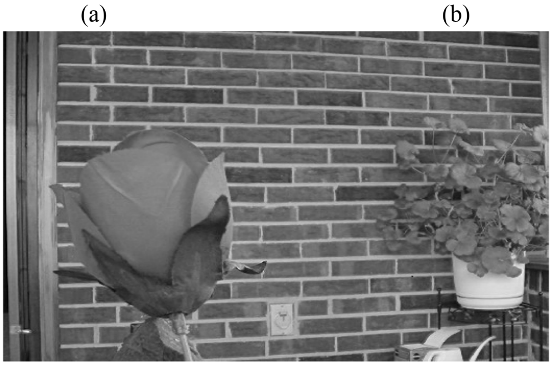


(c)

Fig. 3. a) Left focused image, b) Right focused image, c) All-in-focused image for book image

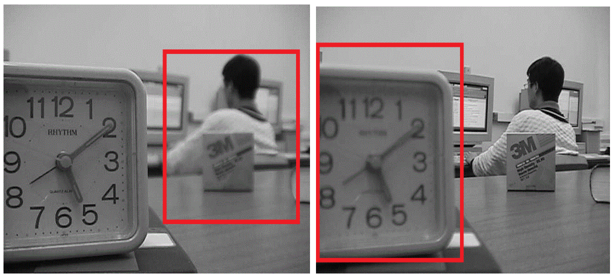


(a) (b)

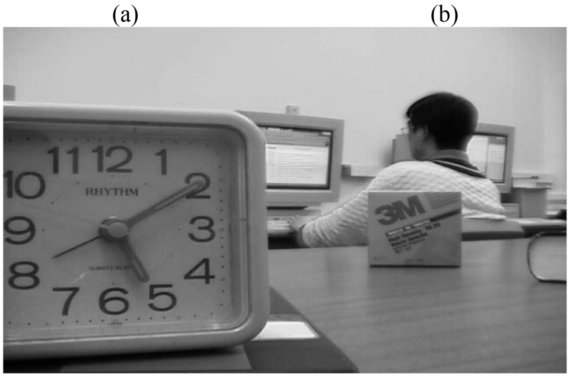


(c)

Fig. 4. a) Left focused image, b) Right focused image, c) All-in-focused image for flower image



(a) (b)



(c)

Fig. 5. a) Left focused image, b) Right focused image, c) All-in-focused image for desk image

(a) (b)

(c)

Fig. 6. a) Left focused image, b) Right focused image, c) All-in-focused image for lytro image

Tests are done with different images and results are calculated using quality metrics in Table 1.

Table 1. Quality Metrics

Image	SD	SF	MI	QAB/F
lab	50,65	8,43	6,83	0,84
book	67,23	20,23	7,57	0,81
cameraman	65,63	20,75	7,10	0,79
clock	65,2	7,44	6,10	0,78
flower	40,66	14,61	5,04	0,79
desk	51,71	11,41	5,96	0,84
pepsi can	77,14	9.8531	6,78	0,81
Girl	79,87	35,59	7,56	0,82
lytro	50,09	13,43	6,44	0,88

7. Conclusions

Multi-focus image fusion is implemented with different methods. We proposed a new hybrid method using Stationary Wavelet Transform (SWT) with Principal Component Analysis (PCA). This hybrid method has not been implemented for multi-focus image fusion before. The tests of this hybrid method are done with different images (color and grayscale). The images are popular images in literature. Mutual Information, Standard Deviation, Spatial Frequency and Petrovic's Metric are used as quality metrics.

The hybrid method is compared with other methods using some quality metrics. This comparison is shown Table 2. In Table 2, 'X' shows the metric which is not calculated for this algorithm. The best results are shown with bold.

Table 2. Comparisons

Methods	clock			pepsi can		
	MI	QAB/F	SD	MI	QAB/F	SD
SWT+PCA	**6,10**	**0,78**	**65.2**	**6,78**	**0,81**	**77.14**
DWT	5,58	0,51	50.7335	5,10	0,52	44.0932
SWT	X	0,59	50.7341	X	0,55	44.1003
PCA	4,87	0,58	44.0054	4,79	0,67	44.0054
Pixel Averaging	X	0,66	50.69	X	0,64	43,63

Also, MI that one of the quality metrics is measured for lab image. MI of lab image is 6, 83 for the hybrid method. This value is compared with other methods [9] for same image. These results are 6.6182 for DWT, 6.6366 for aDWT and 6.7882 for PCA.

And results prove that the hybrid technique is successful according to other methods in this area.

8. References

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