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An Innovative Methodology for Fusing Multifocus Images using Content Adaptive Blurring and Stationary Wavelet Transform

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Abstract: ***This paper depicts a stationary wavelet transformation based image fusion technique in association with content adaptive blurring. The fusion technique combines several images of the same sight or object with diverse resolution, intensity to get a combined image with more suitability for extracting features which is difficult to find from an image in various modalities. The performance and relative importance of the proposed fusion technique is investigated by some statistical evaluation measures. The values of the statistical measure suggests that the execution of the proposed strategy is appreciable. All the test and analysis compared with the different methods yields that the suggested fusion methodology successfully manages to retain the maximum content of the visual truth***

Keywords: Content adaptive blurring, Image Fusion, Multi Focus Images, Stationary wavelet transformation

I. INTRODUCTION

In the area of data fusion multi-focus image fusion has turned to be a vital research [1]. Image fusion technique is a very important part of image processing. In this technique, multi-focus imageries of the identical sight are taken to have a resultant which shows more information of the sight than the distinct input imageries [2]. Thus the informative resultant image is further carried for some post processing. The resulted fused image depicts valuable data content of a scene which will be further beneficial segmentation, feature selection and extraction. Image fusion has wide application in biomedical image processing, computer vision, remote sensing, robotics and microscopic imaging [2].

Generally data fusion is categorised into three levels such as feature level fusion, decision level fusion and pixel level fusion. These fusion levels have distinct algorithms with various applications. In Feature level fusion feature extraction is a prerequisite and as per the extracted features fusion algorithm is decided. Symbol level fusion enables data of different source imageries to be utilized successfully at most elevated amount of deliberation. Usually the input imageries are independently handled for abstraction of valuable information and characterization. Throughout the decades, Pixel-level fusion has pulled in an immense arrangement of research consideration [2].

Various multi-focus fusion strategies were projected in previously. In light of their area, the methodologies are sorted into two categories: transform and spatial area methods [3]. Transform domain combination techniques are exceptionally well known in the previous years as they are proved as more natural methodology towards the issue. Usually the combination techniques in transform domain is carried out in three stages: (i) the input imageries from 'spatial domain' are changed over into 'transform domain'. (ii) Thereafter as per the specific fusion rule the transform coefficients are intertwined to get compound coefficients, lastly these compound coefficients are again retrieved back in spatial space to get the melded picture [1]. DWT, SWT and other pyramid based deterioration are the examples of such changes. Usually high research efforts is received in spatial domain image fusion. Thus as a result various fusion algorithms are evolved which is directly operated on the source images without changing their representation [1].These techniques apply a combination rule on the images to yield a well-focused image. The fusion techniques in spatial space fuse source imageries using locally selected features, for example angle, recurrence, and local standard inference [3]. The transformation specified here is named as un-decimated wavelet transform or stationary wavelet transform (SWT). The SWT is like a DWT yet the distinction is that in the hierarchy there is no down sampling. Hence the resulted sub-images have indistinguishable resolution with the input image. The suggested novel fusion approach conglomerates the efficacies of discrete wavelet transformation and Content Adaptive Blurring (CAB) methods. The paper is systematized as: In section 2, there is brief introduction on content adaptive blurring algorithm. Section 3 deals with the novel fusion approach and eventually the simulated results are illustrated in section 4.

II. CONTENT ADAPTIVE BLURRING

The CAB is a block-based obscuring technique incites obscure on a pixel just if the neighbourhood eminence around that pixel isn't corrupted underneath a specified threshold [1]. Spatial space obscuring is generally resulted by convolution of a smoothing kernel with the input image. If I_s be the original source multi-focus image, and I_{bl} the obscured image obtained by the convolution process by a weighted average smoothing filter in a trivial neighbourhood in I_s .

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$$I_{bl}(s,t) = \sum_{i=-p}^{p}\sum_{j=-p}^{p} w_{i,j} I_s(s+i,t+j) \quad (1)$$

w justifies the smoothing kernel of size (2p+1)x(2p+1) .
According to the Content Adaptive Blurring (CAB) method given a variable focused image, the CAB obscures it by (1) and determines region based mostly correlated coefficient among the initial image and the obscured image by the following expression (2).

$$\hat{\rho}_{bl,s}(s,t) = \sum \frac{w_{i,j}\sigma_s(s+i,t+j)}{\sigma_{bl}(s,t)} \rho_{bl,s}(s+i,t+j) \quad (2)$$

Where $\rho_{bl,s}$ is the correlation between the blocks r_s and r_{bl} and is calculated as follows

$$\rho_{bl,s} = \sum_{i=1}^{m}\sum_{j=1}^{n} \frac{(r_{bl}(s+i,t+j)-\mu_{bl})(r_s(s+i,t+j)-\mu_s)}{\sigma_{bl}\sigma_s} \quad (3)$$

with $$\sigma_{b,l} = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}(r_{bl}(s+i,t+j)-\mu_{bl})^2} \quad (4)$$

and $$\sigma_s = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}(r_s(s+i,t+j)-\mu_s)^2} \quad (5)$$

μ_s , $\mu_{b.l}$ are the means of block r_s and r_{bl} respectively.
A threshold λ is selected and the block having correlation not as much as λ have shown critical quality loss. The content of the image at these regions is re-established once again by the source image and thereafter further obscuring is exempted in the following cycle. The algorithm takes into consideration a multi-focus image Is, with block size (m, n) as input.

III. PROPOSED NOVEL FUSION APPROACH

The proposed approach combines the detailed informative data of both the two source imageries and conserves their spectral characteristics. In the proposed method; pixel level fusion is carried out. Fig. 1 illustrates a framework for the proposed fusion based on SWT and Content Adaptive Blurring.

- Initially both the registered input images are transformed by SWT , and we get approximate details with low frequency, $A^{\alpha}A(2^i;p,q)$, $A^{\alpha}B(2^i;p,q)$ and $D^{\alpha}A(2^i;p,q)$, $D^{\alpha}B(2^i;p,q)$, as high frequency detail parts, i signifies the greatest disintegration level, α=1,2,3,4……. four deterioration portions of the specific goals .
- Then, content adaptive blurring algorithm is applied on every individual detail coefficients independently by taking every detail sub-imageries as an individual block.
- Let Aα and Bα are referred as the αth detail sub-image blocks of the two source images A and B respectively.
- Thereafter the non-uniformly blurred images Ib,1and Ib,2 are resulted using CAB technique and their absolute difference Id,1 and Id,2 with equivalent input images is determined.

$$I_{d,1} = |I_{o,1} - I_{b,1}|$$
$$I_{d,2} = |I_{o,2} - I_{b,2}| \quad (6)$$

- The decision maps $I_{m,1}$ and $I_{m,2}$ are the focused regions found by thresholding the difference map images obtained in the previous step are used to incorporate the input images $I_{o,1}, I_{o,2}$ to get the fused image as per the ensuing rule::

$$I_f(p,q) = \begin{cases} \dfrac{I_{o,1}(p,q)I_{m,1}(p,q) + I_{o,2}(p,q)I_{m,2}(p,q)}{\lambda} & if \lambda > 0 \\ \dfrac{I_{o,1}(p,q) + I_{o,2}(p,q)}{2} & otherwise \end{cases} \quad (7)$$

Where $\lambda = I_{m,1}(p,q) + I_{m,2}(p,q)$ (8)

and the low frequency approximate part is

$$F^{\alpha}(2^i;p,q) = w_1 A^{\alpha}A(2^i;p,q) + w_2 A^{\alpha}B(2^i;p,q)$$
(9)

Where, w1, w2 are two constants chosen in such a way that w1+w2=1.

- Ultimately the final image was resulted by applying inverse SWT transformation on the fused image.

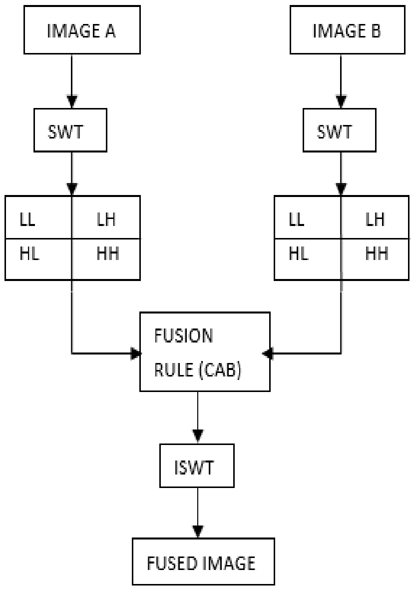

Fig. 1: Proposed novel fusion approach

IV. EXPERIMENTAL RESULT AND PERFORMANCE COMPARISION

In the proposed approach of fusion two multi-focused input images are considered. The source images are co-registered in such a way that pixel alignment in both the images will be area specific. Thereafter the two registered images are taken care by the proposed fusion approach.

The quantitative analysis of the suggested technique is analysed on 4 pairs of diverse source imageries, of size 512x512 namely, A, B, C and D as shown in fig. 2, 3; fig. 6, 7;fig. 10,11 and fig. 14, 15 respectively. The result obtained by the proposed method is presented in fig 5 9,13 and 17, and the result of content adaptive blurring method is presented in fig. 4, 8, 12 and 16 for A, B, C and D respectively. PSNR, correlation coefficient and deviation constants are some chosen statistical parameters whose value evaluates the performance of the fusion algorithm. The brief description of the selected parameters are as follows

A. Peak Signal To Noise Ratio (PSNR)

Qualitative analysis for the resulted fused image is usually assessed by visual analysis and PSNR is measured here to quantify it. PSNR is dependent on RMSE, which can be determined as

$$RMSE = \sqrt{\frac{\sum_{s=1}^{p}\sum_{t=1}^{q}\left[R_i(s,t) - F_i(s,t)\right]}{p \times q}} \tag{10}$$

Where, the standard reference image is expressed as Ri and the resultant image of the fusion process as Fi.

$$PSNR = 10 \times \ln\left(\frac{Pix_{\max} \times Pix_{\max}}{RMSE^2}\right) \tag{11}$$

Pix_{max} is the maximum pixel value from the dynamic range of the resultant image. Consequently, higher value of PSNR, suggest an improved process of fusion.

B. Deviation Index (DI)

It is determined as per the following expression

$$DI = \frac{1}{p \times q}\sum_{i=1}^{p}\sum_{j=1}^{q}\frac{\left|I_R(i,j) - I_F(i,j)\right|}{I_R(i,j)} \tag{12}$$

The gray level value of the selected standard focused image and the fused image at the location (i,j) is represented as I_R and I_F respectively. As a result, lower the value of DI, suggest an improved fusion process.

C. Correlation Coefficient (CC)

It is determined from the following defined expression

$$CC(F,R) = \frac{\sum_{i,j}\left|(I_F(i,j) - \mu_F) \times (I_R(i,j) - \mu_R)\right|}{\sqrt{\sum_{i,j}(I_F(i,j) - \mu_F)^2 \times \sum_{i,j} I_R(i,j) - \mu_R)^2}} \tag{13}$$




Fig 2:Left focused A image

Fig 3:Right focused A image

Fig 4:CAB based fused image

Fig 5: Proposed fused image




Fig 6:Left focused B image

Fig 7:Right focused B image

Fig 8:CAB based fused image

Fig 9: Proposed fused image




Fig 10 :Left focused C image

Fig 11:Right focused C image

Fig 12:CAB based fused image

Fig 13: Proposed fused image

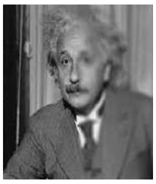
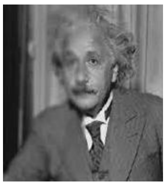
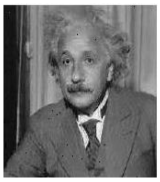
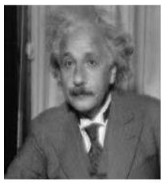

Fig 14:Left focused D image

Fig 15:Right focused D image

Fig 16:CAB based fused image

Fig 17: Proposed fused image

It measures the resemblance of the resulted fused image and the reference image

Where, $I_F(i,j)$, $I_R(i,j)$ justifies the intensity at the location (i,j) of the two fused and reference images . μ_F and μ_R is the mean of the two images F and R respectively.

Table-I: Performance statistical parameters of images

Image Name	Method	PSNR	Correlation coefficient	Deviation index
A	*Wavelet (SWT)*	19.086	0.765	0.4956
	Content Adaptive blurring (CAB)	22.2238	0.9090	0.0943
	Proposed Method	33.1341	0.9924	0.0287
B	*Wavelet (SWT)*	16.1642	0.6722	0.6140
	Content Adaptive blurring (CAB)	18.7423	0.8274	0.1651
	Proposed Method	29.8153	0.9874	0.0847
C	*Wavelet (SWT)*	20.3304	0.6558	0.1263
	Content Adaptive blurring (CAB)	24.4775	0.8719	0.0482
	Proposed Method	32.1998	0.9804	0.0333
D	*Wavelet (SWT)*	21.0212	0.7088	0.4848
	Content Adaptive blurring (CAB)	21.4339	0.8560	0.1617
	Proposed Method	29.2408	0.9769	0.0838

V. CONCLUSION

The suggested process conserves the spectral characteristics of the resulted uniformly focused fused image. The approach integrates qualitatively the spatial details of the two source images. The quantitative evaluation metric illustrates that the proposed technique of image fusion is value-added significantly as compared to alternative existing ways.

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