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# MULT IFOCUS IMAGE FUSION SCHEME USING A COMBINATION OF NONSUBSAMPLED CONTOURLET TRANSFORM AND AN IMAGE DECOMPOSITION MODEL

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**ABSTRACT**

In this paper, a novel image fusion algorithm based on the non subsampled contourlet transform (NSCT) and an image decomposition model (IDM) is proposed, aiming at solving the fusion problem of multifocus images. In order to select the coefficients of the fused image properly, the selection principles for different sub bands are discussed, respectively. For choosing the low frequency sub band coefficients, maximum local energy is used as the focus measure to fuse the low frequency sub band. When choosing the high frequency subband coefficients, the maximum absolute value is used as the activity-level measurement to select coefficients from the high frequency sub images. Experimental results demonstrate that the proposed algorithm outperforms typical wavelet-based, no subsampled contour let-based fusion algorithms in terms of objective criteria and visual appearance.

**Keywords** *: Non Subsampled, Wavelet, Image Fusion, Multi Scale Transform, Image Decomposition Model, Local Energy.*

## 1. INTRODUCTION

The image focusing everywhere contains more information than those which just focus one objet. This type of images is widely used in many fields such as remote sensing, medical imaging, computer vision and robotics. In practice, all cameras used in computer vision systems are not pin-hole devices but consist of convex lenses. Therefore, they suffer from the problem of limited depth of field [1]. It is often not possible to get an image which contains all relevant objects in focus. The objects in front of or behind the focus plane would be blurred. One way to overcome this problem is by image fusion, in which several images with different focus points are combined to produce an image with all objects fully focused [2]. A number of techniques for mult ifocus image fusion have been proposed during the last decade.The simplest mult ifocus image fusion method in spatial domain, which is to take the average of the source images pixel by pixel, would lead to several undesired side effects such as reduced contrast [3]. Various methods based on multiscale decomposition (MSD) have been proposed recently [4, 5, 6, 7]. In MSD domain, the discrete wavelet transform (DWT) becomes the most popular and important multiscale decompositions (MSD) method in image fusion. The reason that the DWT has many advantages, such as localization and direction, over the pyramid transform, the DWT-based methods are generally superior to the pyramid-based methods [7]. Wavelet transform is optimal tool for one-dimensional piecewise smooth signals, however it has serious limitations in dealing with high dimensional signal like images. 2D separate wavelet is only good at isolating the discontinuities at objet edges, but cannot effectively represent the line and the curve discontinuities. On the other hand, it can only capture limited directional information. So, WT based fusion scheme cannot preserve the salient features in source images efficiently, and will probably introduce some artifacts and inconsistency in the fused results [6]. Contourlet Transform (CT) proposed by Minh N. Do and Vetterli [8] is a true two dimensional image representation method. It is achieved by combining the LP [9] and the directional filter bank (DFB) [10]. Compared with the traditional DWT, the CT is not only with multi-scale and localization, but also with mulit-direction and anisotropy. As a result, the CT can represent edges and other singularities along

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curves much more efficiently. However, the CT lack of shift-invariance and results in artifacts along the edges to some extend. In 2006, Cunha, et al. proposed an overcomplete transform, namely, the nonsubsampled contourlet transform (NSCT) [11]. The NSCT inherits the perfect properties of the CT, and meanwhile possesses the shiftinvariance. When the NSCT is introduced into the image fusion field, more information for fusion can be obtained and the impacts of misregistration on the fused results can also be reduced effectively. So, the NSCT is more suitable for image fusion.

In this paper, a new image fusion algorithm, which based on a combination of both NSCT and an image decomposition model (IDM) into geometrical and texture (oscillatory) components, is proposed. After decomposing the original images into two components using IDM, each component is decomposed into its subband coefficients by using NSCT. The coefficients of the frequency bands are treated with different ways based on maximum local energy scheme and the maximum absolute value. The fused image can then be achieved by an inverse contourlet transform with the coefficients obtained from all frequency bands. Both qualitative and quantitative performance evaluations are made and verified in the paper.

The structure of this paper is as follows: Section 2 describes Nonsubsampled contourlet transform while section 3 describes the image decomposition model. Section 4 and 5 present the proposed image fusion method and also provide an experiment study respectively. Finally, a conclusion of the paper is given.

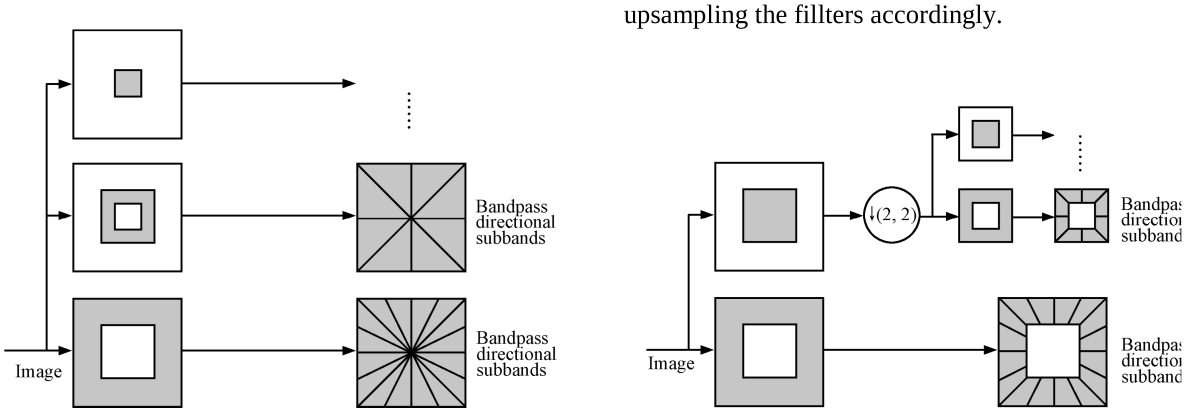
## 2. NONSUBSAMPLED CONTOURLET TRANSFORM

### 2.1 Contourlet transform

Controurlet transform (CT) [8] is a kind of multiresolution analysis tool, which is based on nonseparable filter banks and provides an efficient directional multiresolution image representation. In the contourlet transform, the Laplacian pyramid (LP) is first used to capture the point discontinuities, and then followed by a direction filter banks (DFBs) to link point discontinuities into linear structures. Compared with the traditional DWT, the CT is not only with multiscale and localization, but also with multidirection and anisotropy. So the CT can represent edges and other singularities along curves much more efficiently. Unfortunately, in the CT, downsampling and upsampling are presented in both LP and DFB as shown in figure (1) (a). Thus the CT is lack of shift-invariance and causes pseudo-Gibbs phenomena around singularities.

Cunha, Zhou, and Do [11] proposed nonsubsampled contourlet transform (NSCT), which aims to overcome the disadvantage of CT. figure(1) (b) shows the decomposition framework of NSCT.

Nonsubsampled pyramid structure (NPS) and nonsubsampled DFB are employed in NSCT. The NPS is achieved by using two-channel nonsubsampled 2-D filter banks. The DFB is achieved by switching off the downsamplers/upsamplers in each two-channel filter bank in the DFB tree structure and upsampling the fillters accordingly.




(a)Contourlet (b) NSCT

*Figure (1) : Decomposition framework of contourlet and NSCT.*

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## 3. DECOMPOSITION MODEL

In recent decades, the combination of image processing, vision analysis, and mathematics has given rise to a new discoveries as well as revived various classical subjects, e.g., wavelets, multiresolution analysis, oscillatory patterns, fractals, moving fronts, multiphase problems with free boundaries, and Gibbs' random fields. Mathematics has provided the solid ground for solving many challenging imaging and vision problems in a unified and mass-production manner.

Removing noise in an image has always been a challenging task because of the difficulty of identifying noise from useful information. A lot of linear filtering algorithms have been used, such as simple Gaussian smoothing/Fourier domain low pass filtering, to more advanced Tikonov regularization [12] and wavelet denoising. Although these methods are very fast, they tend to smooth out edges of an image. A number of non-linear filters were thus developed to remedy the edge smearing effects.

Total Variation (J) regularization [13] (invented by Rudin, Osher and Fatemi (ROF)) is edge-preserving : it allows discontinuous solutions which best fit the noisy image.

Let u be the true image and f the distorted image. Then the model of ROF to solve is:

$$\min_u \left\{ \alpha J(u) + \frac{1}{2}\|u - f\|_2^2 \right\}$$

where

$$J(u) = \int_\Omega |\nabla u| \, dx$$

$\nabla$ denotes the spatial gradient.

$\alpha$ measures the tradeoff between the regularization and the best fit to the noisy data.

This model decompose an image f into a component u and a component v = f – u, which is supposed to be the noise. In [14], Meyer out some limitations of the ROF model. He proposes a different decomposition which he believes in more a adapted:

$$\inf_{(u,v)\in BV\times G\,/f=u+v} \{J(u) + \alpha\|v\|_G\}$$

Where BV is the space of functions of bounded variation [14] and G is the space of oscillating functions (in particular textures and noise) introduced by Yves Meyer [14].

Inspired by this works, many numerical algorithms have been developed to carry out the decomposition of grayscale images [15, 16, 17].

In this article, we adopt the algorithm proposed by Vese et all [16] to solve Meyer'model. It is construct by minimizing a convex functional which depends on the two variables u and v, alternately in each variable. Each minimization is based on a projection algorithm to minimize the total variation.

Thus decomposition is given by minimizing a functional F

$$F_{\lambda,\mu}^{OV}(u,g) = J(u) + \lambda\|f - (u + \mathrm{div}(g))\|_{L^2}^2 + \mu\left\|\sqrt{g_1^2 + g_2^2}\right\|_{L^p}$$

where

$$g = (g_1, g_2) \in L^\infty \times L^\infty ;\, v = \mathrm{div}\, g$$

$u \in BV$ containing the structure of the image, a second one, $v \in G$ the texture. Where J(u) is the total variation related to the extraction of the geometrical component,

where $\lambda$, $\mu > 0$ are tuning parameters.

In figure 2 we illustrate the results of this algorithm with $\mu = 0.1, \lambda = 0.001$.

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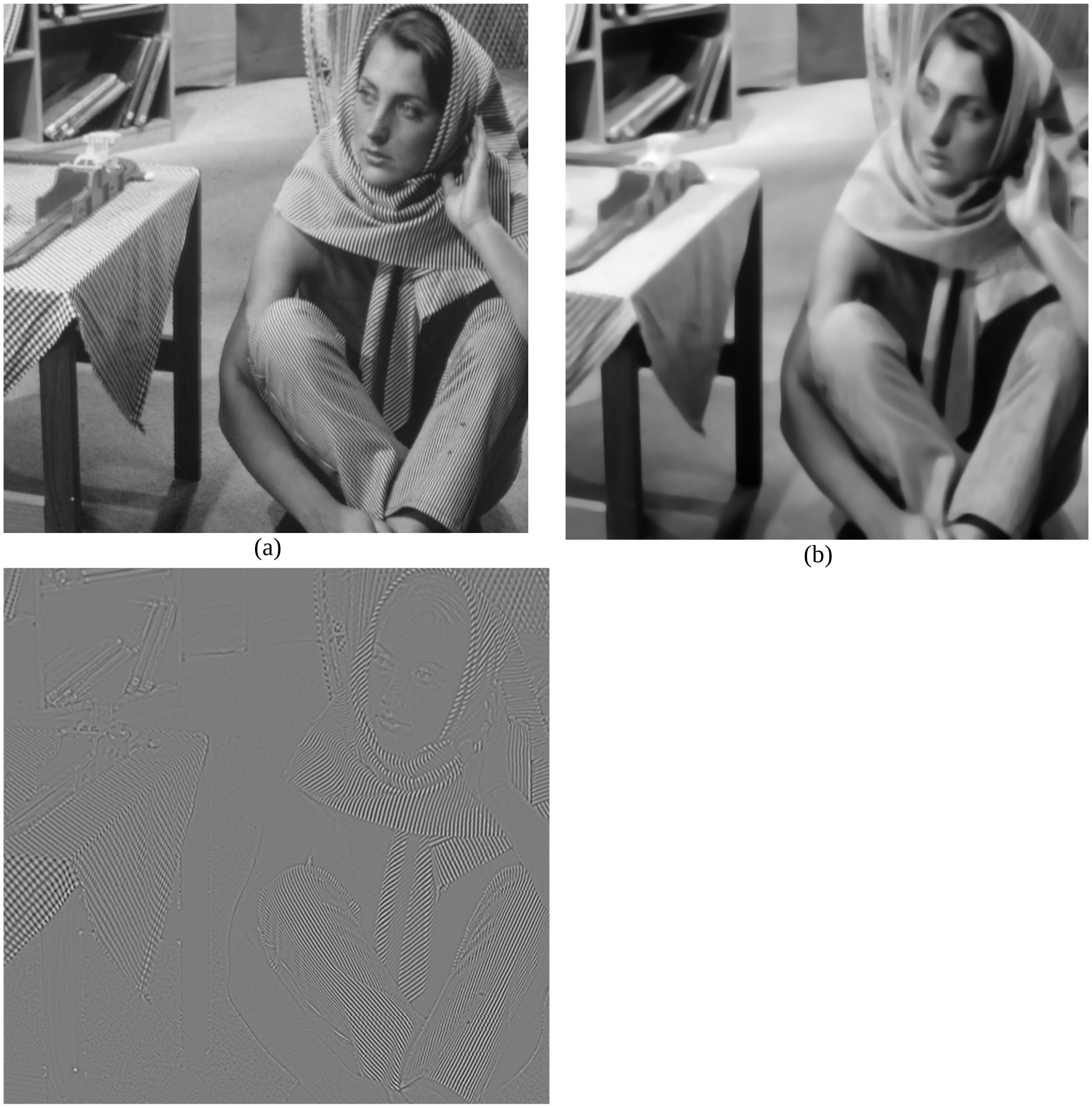

(a) (b)

(c)

*Figure 2: (a) original image, (b) geometrical component, (c) texture component.*

## 4. PROPOSED IMAGE FUSION METHOD

The fusion process, as shown in Figure (3), is accomplished by the following steps:

(1) The original mult ifocus images should be geometrically registered to each other. In this paper, both mult ifocus images A and B are assumed to be registered in preprocessing.

(2) Each of the source images is decomposed by the mathematical model into two components; texture components and geometrical components

(3) Decomposing each component into one low-frequency sub-image and a series of high-frequency sub-images at $L$ levels and $I_d$ directions via NSCT.

(4) The coefficient subbands derived from texture components are fused via Fusion rule- Maximum of absolute value ,

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while coefficient subbands derived from geometrical components are fused via maximum local energy method.

(5) Summing the coefficient subbands of texture components and the coefficient subbands of texture components.

(6) Reconstruct the original image based on the new fused coefficients of subimages by taking an inverse NSCT transform, and then the fused image is obtained.

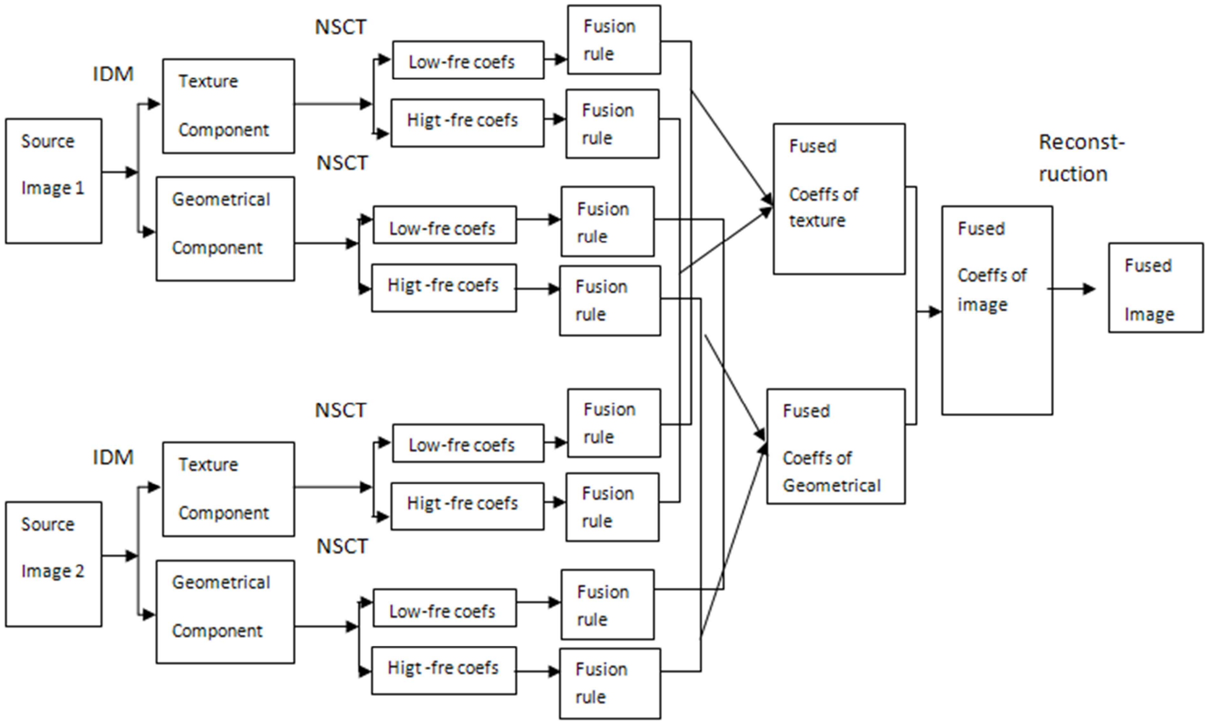


*Figure 3 : Schematic diagram of the proposed image fusion method.*

## 5. EXPERIMENTS AND ANALYSIS

In this section, experimental results of the proposed image fusion method are given and evaluated by comparing with the results obtained by using wavelet transform and Nonsubsampled contourlet transform.

### 5.1 Performance measures

In this paper, we use the mutual information (MI) [18] and $Q^{AB/F}$ [19] to evaluate the performance of the proposed fusion method. MI is defined as the sum of mutual information between each input image and the fused image. $Q^{AB/F}$ metric, proposed by Xydeas and Petovic [19], which considers the amount of edge information transferred from the input images to the fused image. In this method, a Sobel edge detector is used to calculate strength and orientation information at each pixel in both source and the fused images. For both criteria, a larger value would indicate a better fusion result.

### 5.2 Experimental setups

For the wavelet-based fusion method, the wavelet basis 'db1' and a decomposition level of 3 are used. In the Nonsubsampled contourlet transform, the LP filter is 'pkva' and DFB is '9–7' type, the decomposition level L of the LP is three, and the number of directions $I_d$ of the DFB is four. The average and maximum rules are used in the low-frequency and high-frequency domain, respectively. For fair comparison, the same parameter settings are used in our proposed algorithm.

### 5.3 Fusion results

The experiments are performed on the mult ifocus 'leopard' images, the mult ifocus 'cup' images and the mult ifocus 'disk' which shown in Figure (4). (a, b), (c, d) and (e, f), respectively.

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Figs. 5, 6 illustrate the fusion results obtained by the DWT methode, NSCT method and the proposed. To make better comparisons, the difference images between the fused images and the source images, which shown in Fig.4 (a) and (b), are given in Fig.5 (d)–(f) . From Fig. 5(d)–(f) one can obviously find that the fused images of two shift-invariant methods, NSCT and proposed method are clearer and more natural than the DWT fused results. It is proven that shift-invariant methods can overcome pseudo-Gibbs phenomena successfully and improve the quality of the fused image around edges. The values of MI and $Q^{AB/F}$ of Figs. 5 and 6 are listed in Table 1. We observe that the proposed method provides a better performance and outperforms the discrete wavelet transform and NSCT

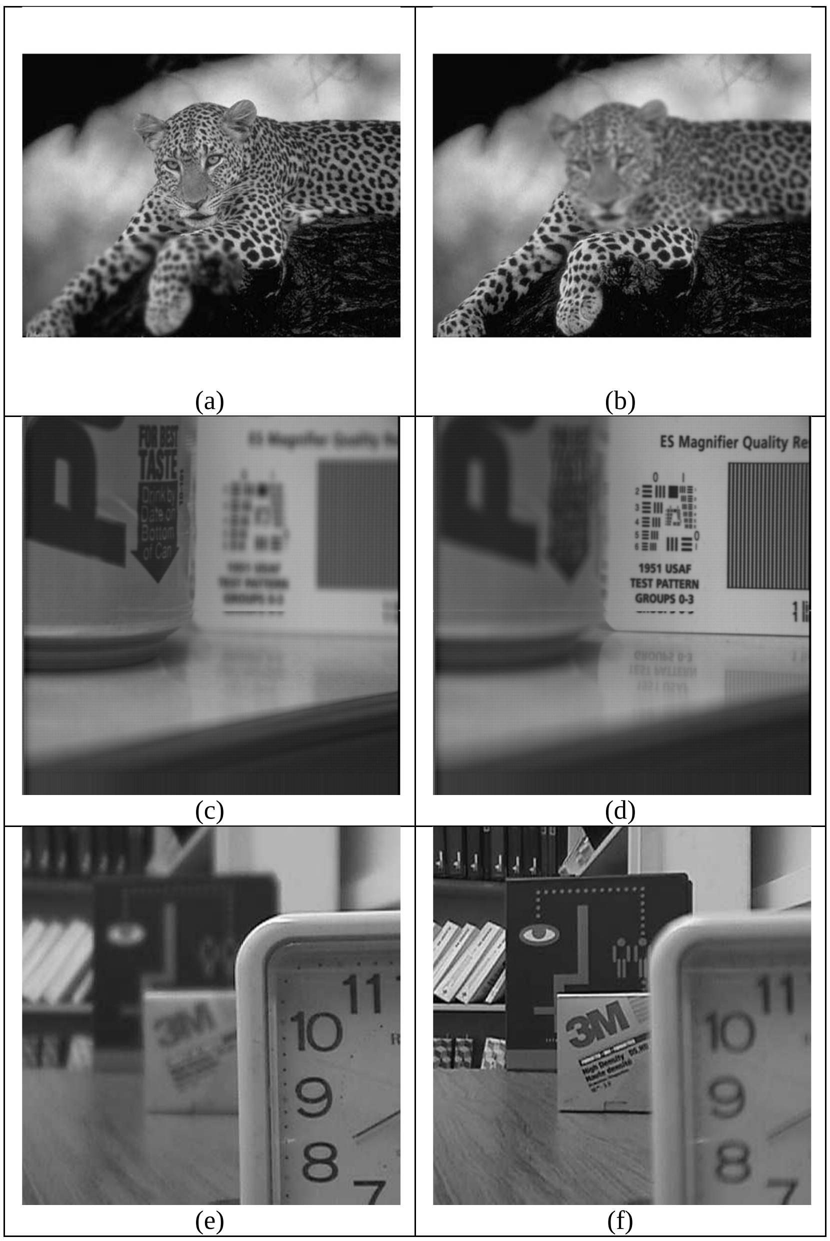


*Fig. 4. Source images for mult ifocus fusion*

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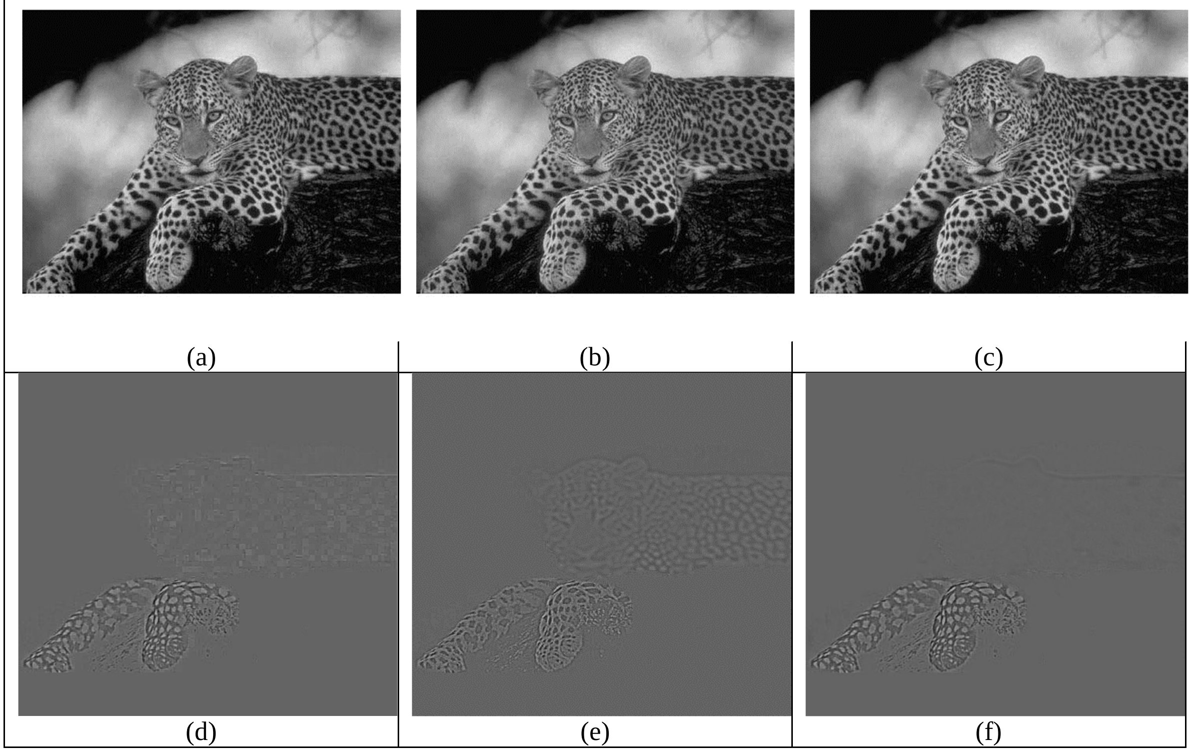


*Figure 5 : Mult ifocus image fusion results:a-c Fused images using WT, NSCT and Proposed method respectively. (d) Difference image between Fig. 5 (a) and Fig. 4 (a), (e) Difference image between Fig. 5 (b) and Fig. 4 (a);(f) Difference image between Fig. 5 (c) and Fig. 4 (a).*

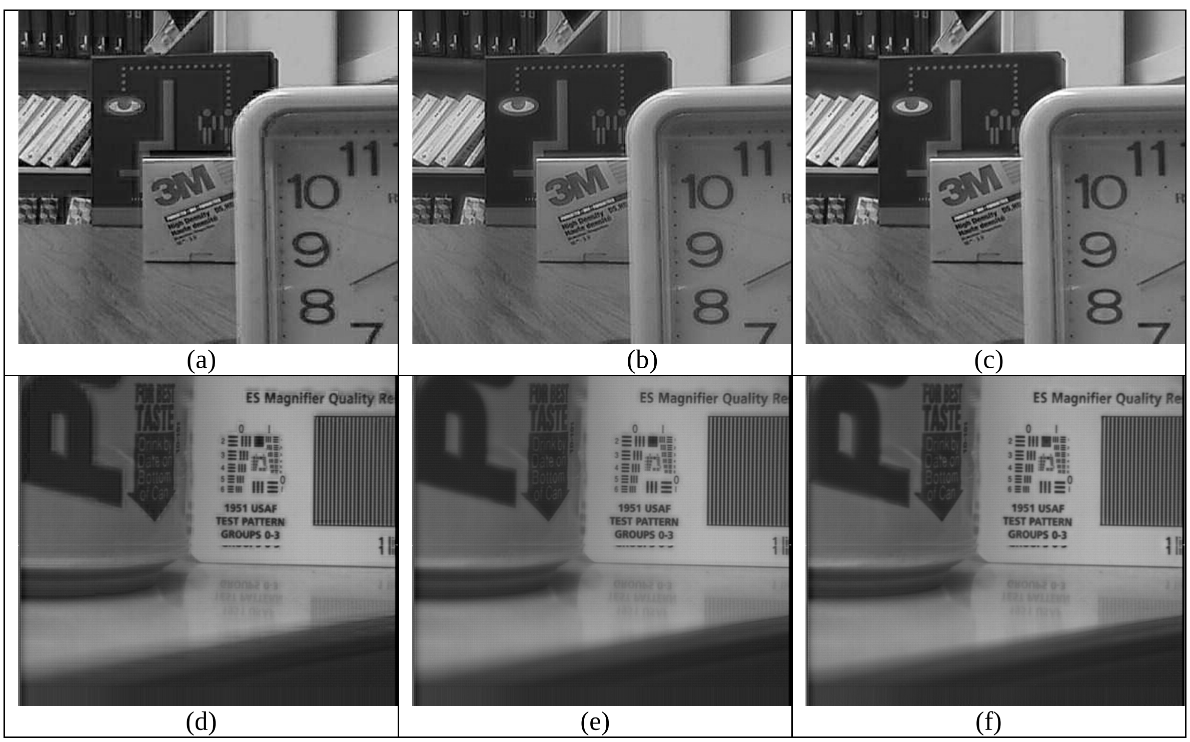


*Figure 6: Mult ifocus image fusion results: Fused images using WT, NSCT and Proposed method respectively*

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*Table 1 Performance of the different fusion methods on processing Fig. 6(a) and (b), Fig. 6(e) and (f).*

| Image | Criteria | WT | NSCT | Proposed Method |
|---|---|---|---|---|
| Leopard | MI | 8.1832 | 8.2175 | 8.6491 |
| | $Q^{AB/F}$ | 0.8180 | 0.8390 | 0.8457 |
| Cup | MI | 6.5399 | 6.7536 | 6.8830 |
| | $Q^{AB/F}$ | 0.7030 | 0.7430 | 0.7510 |
| Disk | MI | 5.8951 | 5.8266 | 5.9250 |
| | $Q^{AB/F}$ | 0.6401 | 0.6501 | 0.6771 |

## 6. CONCLUSION

In this paper, a combined mult ifocus image fusion method was proposed by considering the complementary property of the two different methods. In our algorithm, firstly, each of the registered images are decomposed into two components by using an image decomposition model, then the components are decomposed by using Nonsubsampled contourlet transform and the fused coefficients are reconstructed by performing the inverse using Nonsubsampled contourlet transform. The experimental results on several pairs of mult ifocus image showed that the proposed method has better performance than the wavelet-based fusion algorithm and Nonsubsampled contourlet based fusion algorithm.

## REFRENCES

[1]. Li, S., Kwok, J., Tsang, I., Wang, Y. Fusing images with different focuses using support vector machines. IEEE Trans. Neural Networks, 2004, 15 (6): 1555–1561.
[2]. Zhang, Z., Blum, R.S. A categorization of multiscale-decomposition-based image fusion schemes with a performance study for a digital camera application. Proc. IEEE, 1999, 87 (8):1315–1326.
[3]. S. Li and B. Yang. Mult ifocus image fusion using region segmentation and spatial frequency. Image and Vision Computing, 2008, 26 (7) :971-979.
[4]. G. Pajares, J. Cruz. A wavelet-based image fusion tutorial. Pattern Recognition, 2004, 37 (6): 1855-1872.
[5]. I. De, B. Chanda. A simple and efficient algorithm for mult ifocus image fusion using morphological wavelets. Signal Processing, 2006, 86 (5) : 924-936.
[6]. L. Yang, B.L. Guo, W. Li. Multimodality medical image fusion based on multiscale geometric analysis of contourlet transform. Neurocomputing, 2008,72 (1–3):203-2011.
[7]. H. Li, B.S. Manjunath, S.K. Mitra. Multisensor image fusion using the wavelet transform. Graphical and Models Image Processing, 1995, 57 (3) : 235–245.
[8]. M.N. Do, M. Vetterli. The contourlet transform: an efficient directional multiresolution image representation. IEEE Transactions on Image Processing, 2005, 14 (12):2091–2106.
[9]. P.J. Burt, E.H. Adelson. The Laplacian pyramid as a compact image code. IEEE Transactions on Communications, 1989, 31 (4):532–540.
[10]. R.H. Bamberger, M.J.T. Smith. A filter bank for the directional decomposition of images: theory and design. IEEE Transactions on Signal Processing, 1992, 40(4):882-893.
[11]. A.L. da Cunha, J.P. Zhou, M.N. Do. The nonsubsampled contourlet transform: theory, design, and applications. IEEE Transactions on Image Processing, 2006, 15 (10): 3089–3101.
[12]. Tikhonov, A. N. V. Y. Arsenin.. Solution of Ill posed Problems. Washington: Winston andSons, 1977.
[13]. L. Rudin, S. Osher, End E. Fatimi. Nonlinear total variation based noise removal algorithms. Physica D, 1977, 60:259-268.
[14]. Y. Meyer. Oscillating Patterns in Image Processing and Nonlinear Evolution Equations. The Fifteenth Dean Jacqueline B. Lewis Memorial Lectures. Vol. 22 of

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

University Lecture Series, AMS, Providence, 2001.

[15]. J.F. Aujol, G. Aubert, L. Blanc-Féraud, and A. Chambolle. Decomposing an image. Application to textured images and SAR images. Rapport technique, Université de Nice Sophia-Antipolis, 2003.

[16]. L. A. Vese and S. J. Osher. Modeling textures with total variation minimization and oscillating patterns. image processing.Journal of scientific computing;2003, 19: 553 – 572.

[17]. S.J. Osher, A. Sole, and L. A. Vese. Image decomposition and restoration using total variation minimization and the H(-1) norm.multiscale modelling and simulation. A SIAM interdisciplinary journal, 2003,1(3): 349-370.

[18]. Qu G H, Zhang D L, Yan P F. Information measure for performance of image fusion. Electronics Letters, 2002, 38(7):313-315.

[19]. Petrovic V, Xydeas C. On the effects of sensor noise in pixel-level image fusion performance. In: Proceedings of the 3rd International Conference on Image Fusion. Paris, France: IEEE, 2000.14-19.