ISSN:0975-9646

Kurakula Sravya et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 5 (4) , 2014, 5393-5396

Image Fusion on Multi Focused Images using NSCT

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Abstract - In this paper we put forward an image fusion algorithm based on Wavelet Transform, Second Generation Curvelet Transform and Nonsubsampled Contourlet Transform. Here we analyze the characteristics of NSCT along with Wavelet and Curvelet Transform for simulation experiments on multi-focus images. Here it includes multiresolution analysis ability in wavelet transform, also has better direction ability for edge feature of awaiting describing image in the second Generation Curvelet Transform and the NSCT is flexible, multiscale, multidirection, and shift invariant image decomposition that can be efficiently implemented in image fusion. The core of the proposed scheme is in NSCT. This paper uses Wavelet, Curvelet and Contourlet Transform into fusion images, then makes deep research on fusion standards and puts forward corresponding fusion project.

Keywords–Image Fusion, Wavelet Transform, Second Generation Curvelet Transform, Nonsubsampled Contourlet Transform (NSCT).

I. INTRODUCTION

Image fusion is the process that combines information in multiple images of the same scene. These images may be captured from different sensors, acquired at different times, or having different spatial and spectral characteristics [1]. The object of the image fusion is to retain the most desirable characteristics of each image. With the availability of multi-sensor data in many fields, image fusion has been receiving increasing attention in the researches for a wide spectrum of applications [2]. Here we use image fusion algorithm based on Wavelet Transform which faster developed was a multiresolution analysis image fusion. It has good time-frequency characteristics [3].

To overcome the limitations of Wavelet Transform we put forward Curvelet Transform which consists of special filtering process and multi-scale Ridgelet Transform [4]. This includes realization, sub-band division, smoothing block, normalization and so on.

To improve the quality of the image at the edges by removing the noise we use Nonsubsampled Counterlet Transform. The construction proposed in this is based on pyramid and directional filters [5]. The NSCT is fully shift-invariant, multiscale, and multidirectional.

II. NONSUBSAMPLED CONTOURLET TRANSFORM

NSCT is a kind of multi-scale and multi-direction computation framework of the discrete images which can be divided into two stages includes Non-Subsampled Pyramid (NSP) and Non-Subsampled Directional filter bank (NSDFB) [6]. The multiscale property using two-channel filter bank, and one low-frequency image and one high-frequency image can be produced at each level of NSP decomposition. The subsequent NSP decomposition stages are carried out to decompose the low-frequency components of the image. The property of NSP is obtained by NSFB structure which is similar to that of Laplacian pyramid which is achieved by using the Nonsubsampled filter banks.

NSCT is shown in Fig 1 with the NSFB structure that implements the NSCT and frequency partitioning.

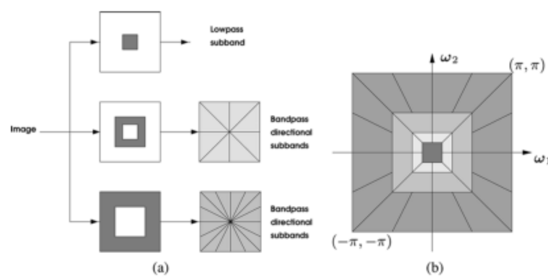


Fig. 1 Non-subsampled Counterlet Transform. (a) NSFB structure that implements NSCT. (b) Idealize frequency partitioning.

Non-Subsampled Pyramid NSP result in k+1 sub-image, which consists of one low-frequency image and k high-frequency images having same size as the source image. Where k is number of decomposition levels [7]. The NSDFB is two-channel non-subsampled filter banks which are constructed by combining the directional filter bank. It allows the direction decomposition with l stages in high-frequency from NSP at each scale and produces 2^l directional sub-images as source image. The NSCT has proven to be very efficient in image denoising and image enhancement, the structure that implements the NSCT by pyramid decomposition [8] and frequency plane for multiresolution expansion is shown in fig 1 which is shown below

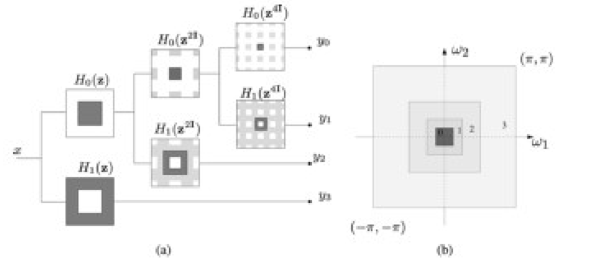


Fig.2 Nonsubsampled Pyramid (a) Three-stage pyramid decompostion. (b) Subband frequency plane.

The NSDFB is constructed by combining critically-sampled two-channel fan filter banks and resampling operations. A shift-invariant directional expansion is obtained with NSDFB [9]. The NSDFB is constructed by eliminating the downsamplers and upsamplers in the DFB. Elimation can be done by switching off the downsampler or the upsampler in the DFB in each filter bank. This is shown in Fig.3 as illustrated below

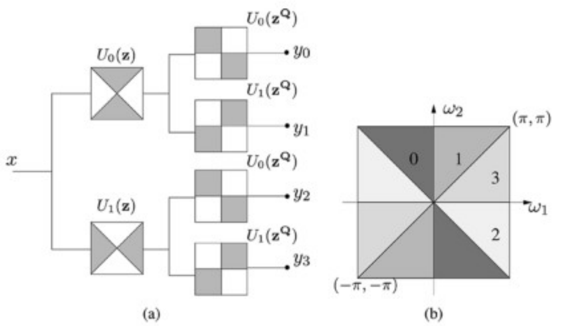


Fig. 3 Nonsubsampled directional filter bank constructed with two-channel fan filter banks. (a) Filtering structure. (b) Corresponding frequency decomposition.

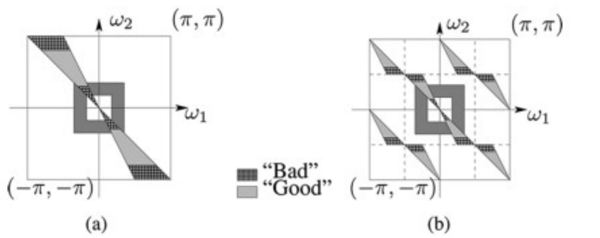


Fig.4 Sampling in the NSCT. (a) With no upsampling. (b) With upsampling.

Here Fig.4 shows the need for upsampling in the NSCT fig (a) shows with no upsampling, the high-pass at higher scales will be filtered by the portion of the directional filter that has "bad" response. Fig (b) shows upsampling ensures that filtering is done in the "good" region. Here in image fusion of NSCT we take a pair of images to generate a composite image. The basic condition in this is that all the source images must be registered n order to align the corresponding pixels.

To perform l-level NSCT on the source images to obtain one low-frequency and a series of high-frequency sub-images at each level and direction θ, i.e.,

$$A{:}\{C_l^A, C_l^A, \theta\} \text{ and } B{:}\{C_l^B, C_l^B, \theta\} \quad (1)$$

Where C_l^* are low-frequency sub-images and C_l^*, θ represents the high-frequency sub-images at level $l \in [1, l]$ in the orientation θ.

Fusion of low-frequency sub-images represents the approximation components of the source images. The easy way is to use conventional averaging method to produce the composite bands. That is first, the features are extracted from low-frequency sub-images denoted by $\mathrm{P}c_l^A$ and $\mathrm{P}c_l^B$. Then fuse the low-frequency sub-images as

$$C_l^F(x,y) = \begin{cases} C_l^A(x,y), & if\ \mathrm{P}c_l^A(x,y) > \mathrm{P}c_l^B(x,y) \\ C_l^B(x,y), & if\ \mathrm{P}c_l^A(x,y) < \mathrm{P}c_l^B(x,y) \\ \frac{\sum_{k \epsilon A,B} C_l^k(x,y)}{2} & if\ \mathrm{P}c_l^A(x,y) < \mathrm{P}c_l^B(x,y) \end{cases} \quad (2)$$

Now fusion of high-frequency sub-images, here the coefficients in the high-frequency sub-images usually include detail component of the source image. And it is also true that noise is also related to high-frequencies and it can cause miscalculation of sharpness value by affecting the fusion performance. To remove this directive contrast is done which is first applied on high-frequency sub-image of NSCT at each scale by $\mathrm{D}c_{l,\theta}^A$ and $\mathrm{D}c_{l,\theta}^B$ at each level $l \in [1, l]$ in the direction θ.

$$C_{l,\theta}^F(x,y) = \begin{cases} C_{l,\theta}^A(x,y), & if\ \mathrm{D}c_{l,\theta}^A(x,y) > \mathrm{D}c_{l,\theta}^B(x,y) \\ C_{l,\theta}^A(x,y), & if\ \mathrm{D}c_{l,\theta}^A(x,y) < \mathrm{D}c_{l,\theta}^B(x,y) \end{cases}$$

(3)

Now perform l-level inverse NSCT on the fused low-frequency (C_l^F) and high-frequency ($C_{l,\theta}^F$) sub-images, to get the fused image (F).

III. IMPLEMENTATION

The steps for the Transform to fuse two images are as follows:

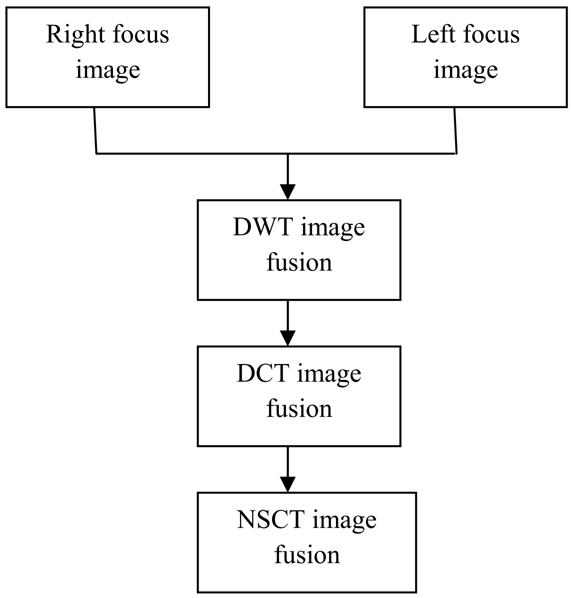


Fig. 5 Flow chart to show the steps involved in image fusion.

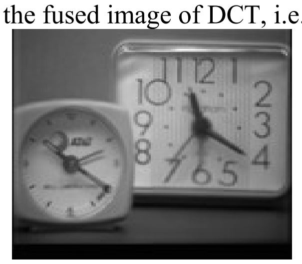
- Resample and registration of original images, with this we can correct original images and distortion so that both of them have similar probability distribution.
- Then the Wavelet coefficient of similar component will stay in the same magnitude.
- Using Discrete Wavelet Transform to decompose original images into proper levels. One low-frequency approximate component and three high-frequency components will be acquired.
- Here in DWT we take two images A, B which are resample and registered where the process of Wavelet Transform takes place and images A and B are also fused.
- These images A and B which are nothing but left-focus image and Right-focus image and after the image fusion of A and B we get fused image of DWT, i.e.,

(A) Left-focus image

(B) Right-focus image

(C) Fused image of DWT

- Now we use the Discrete Curvelet Transform on the output image of the DWT. Here Curvelet Transform of individual acquired low-frequency approximate component and high-frequency detail components from the input images, neighborhood interpolation method is used and the details of gray can't be changed.
- Here after the DWT we use DCT for images know we get the fused image of DCT, i.e.,



(D) Fused image of DCT

- Now we use NSCT to fuse the images in this first we take the image as apply NSCT to get low-frequency and high-frequency sub-images. Then fusion of low-frequency sub-images is done then fusion of high-frequency sub-image is done. After this *l*-level inverse NSCT on the fused low-frequency and high-frequency sub-images is done to get the fused image.

(E) Fused image of NSCT

According to definite standard to fuse images, local area variance is chose to measure low-frequency component. First divide low-frequency $C_{j0}(k1,k2)$ into foursquare blocks which are N_1 XM_1, then calculate the local area variance as

$$STD=\sqrt{\frac{\sum_{i=-(N_1-1)/2}^{(N_1-1)/2}\sum_{i=-(M_1-1)/2}^{(M_1-1)/2}[C_j(k_1+i,k_2+j)-C_j{}'(k_1k_2)]^2}{N_1XM_1}} \quad (4)$$

Where, $c_{j0}^{'}(k_1,k_2)$ stands for low-frequency, coefficient mean of original images. If variance is bigger, then it shows that the local contrast of original image is bigger, this is nothing but

$$C_{j0}^{F}(k_1,k_2)=\begin{cases}C_{j0}^{A}(k_1,k_2), & STD^A \geq STD^B\\ C_{j0}^{B}(k_1,k_2), & STD^A < STD^B\end{cases} \quad (5)$$

The other components activity $E_{jl}(k_1,k_2)$ is defined as a fusion standard of high-frequency components. First, the images are divide high-frequency sub-band into sub-blocks, then calculate the STD of sub-blocks.

$$E_{jl}(k_1,k_2)=\sum_{i=-(N_1-1)/2}^{(N_1-1)/2}\sum_{i=-(M_1-1)/2}^{(M_1-1)/2}[C_{jl}(k_1+i,k_2+j)-C_j{}'(k_1k_2)]^2 \quad (6)$$

The inverse transformation of coefficients after fusion, the reconstructed images will be fused image.

IV. Result and Discussion

We use multi-focus images which are shown in the above section III Right-focus image, Left-focus image and three fusion algorithms are adopted in this paper to contrast fusion effects. We use Discrete Wavelet Transform (DWT), Discrete Curvelet Transform (DCT), and Nonsubsampled Contourlet Transform (NSCT) for image fusion.

We have calculated the following parameters:

- Entropy a scalar value representing the entropy of an intensity image. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as

$$H=-\sum_{i=1}^{n}p_i\times\log_2 p_i$$

Where
H: Entropy of image
N: Gray level of an input image (0-255)
P_i: probability of the occurrence of symbols i.

We adopt Entropy of fused image, correlation coefficient C_{cc} and rms error E_{rms} to evaluate the fused quality, it is expressed as table I. In the same group of experiments, if Entropy of fused image is bigger, or correlation coefficient approach one more closely, or E_{rms} is smaller. It shows that the fusion methods adopted is better

TABLE I- EVALUATION OF THE MULTI-FOCUS IMAGE FUSION RESULT

Fusion Methods	**Entropy**	C_{cc}	E_{rms}
DWT	7.1381	0.99081	0.056812
DCT	7.3592	0.99511	0.044827
NSCT	7.3627	0.99512	0.027391

V. CONCLUSION

In this paper we put forward a better image fusion algorithm based on transformation techniques, Discrete Wavelet Transform, the Discrete Curvelet Transform and Nonsubsampled Curvelet Transform. It includes the multi resolution analysis to check the ability in Wavelet transform, and also has better direction identification ability for the edge feature of awaiting describing images in the non-sub sampled Curvelet Transform. This method could better describe the edge direction of images, and analyzes feature of the fused images better by NSCT. According to this paper we uses a DWT, DCT and also non-sub sampled Curvelet Transform into fusion images and , then makes deep research on fusion standards and this paper puts forward corresponding fusion projects. In vision, the fusion algorithm proposed in this paper acquires better fusion result.

REFERENCES

[1] Chao Rui Zhang Ke Li Yan-jun. An image fusion algorithm using Wavelet Transform [J]. Chinese Journal of Electronics , 2004 , 32 (5):750-753.

[2] Li, H., Manjunath, B.S., Mitra, S.K., 1995. Multisensor image fusion using the Wavelet Transform. Graphical Models Image Process. 57 (5), 235–245.

[3] Huang Xishan , Chen Zhe. A wavelet –based scene image fusion algorithm[C]. Proceedings of IEEE TENCON 2002. Piscateway , USA : IEEE Press , 2002:602-605.

[4] Starck J. L , Candes E. J , Donoho D. L. The Curvelet Transform for image denosing[J]. IEEE Trans Image Process, 2002, 11(6) : 670-684.

[5] E. J. Candes, D.L. Donoho. Curvelets: A A surprisingly effective nonadaptive representation for objects with edges [J]. In:C. Rabut A. Cohen, L. L. Schumaker. Curves and Surfaces. Nashville, TN: Vanderbilt University Press, 2000. 105-120.

[6] E. J. Candes, D.L. Donoho. New tight frames of curvelets and optimal representations of objects with singularities[J]. Commun. On Pure and Appl. Math.2004, 57(2):219-266.

[7] LiHui-hu, I GuoLe, i LiuHang. Research on imae fusion based on the second generation curvelet transform [J]. Acta Optica Sinica, 2006,26(5): 657-662.

[8] Huang Xishan, Chen Zhe. A wavelet- based scene image fusion algorithm[C]. Proceedings of IEEE TENCON 2002. Piscateway, USA: IEEE Press, 2002:602-605.

[9] X. Qu, J. Yan, H. Xiao, and Z. Zhu, "Image fusion algorithm based on spatial frequency-motivated pulse coupled neural networks in nonsubsampled contourlet transform domain," Acta Automatica Sinica, vol. 34, no. 12, pp.1508-1514, 2008.