Multi-focus Image Fusion Using Curvelet Transform

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***Abstract*—Curvelet transform is a new muiti-scale geometic analysis, which has the characteristics of anisotropy. It is more suitable for the analysis of image curve edge characteristics than wavelet. Thus, in this paper it is applied to multi-focus image fusion, and used fusion rules that suitable for the characteristics of multi-focus image fusion.**

Keywords-component; multi-focus image; Curvelet transform style; muiti-scale geometic analysis

I. INTRODUCTION

Multi-focus image fusion is to fuse a completely clear image with a set of images of the same scene and under the same imaging conditions which are with different focus points. Multi-focus image fusion can effectively improve the utilization rate of the image information and the system reliability the target detection and recognition. Therefore, it is widely used in machine vision and target recognition. wavelet transform has been widely used in image processing for its well time-frequency analysis features. But in the characteristics and advantages of one dimensional wavelet analysis cannot simply promotion to two dimension or higher[1]. So E.J.C andes and D.L.Donoho[2-4] proposed Curvelet transform which has the characteristics of direction and anisotropy. in this paper it is applied to multi-focus image fusion. Firstly,curvelet transform was used for image multi-scale decomposition, Secondly, we apply different fusion rules to the corresponding high and low frequency component from the curvelet decomposition. Finally , through the consistency check to get the final fusion image.

II. CURVELET TRANSFORM THEORY

A. Continuous curvelet transform

in 2D space R^2, scales is defined 2^{-j}, the direction Angle is defined θ_l , the position is defined $x_k^{(j,l)} = R_{\theta_l}^{-1}(k_1 \times 2^{-j}, k_2 \times 2^{-j/2})$, then Curvelet function is as follow

$$\varphi_{j,l,k}(x) = \varphi_j(R_{\theta_l}(x - x_k^{(j,l)})) \tag{1}$$

Where R_θ is radian rotation.

Two dimensional Curvelet transform is defined

$$c(j,l,k) =< f, \varphi_{j,l,k} >= \int_{R^2} f(x)\overline{\varphi_{j,l,k}(x)}dx \tag{2}$$

A Cartesian coordinate system signal $f[t_1,t_2], 0 \le t_1 \le t_2 < n$, 2-dimension discrete Curvelet transform is defined

$$c^D(j,\ell,k) = \sum_{0 \le t_1 \le t_2 < n} f[t_1,t_2]\overline{\varphi^D_{j,\ell,k}[t_1,t_2]} \tag{3}$$

B. Discrete Curvelet transform fast algorithm

Candes and Donoho in [5] provides two kind of fast discrete Curvelet transform method, respectively is USFFT transformation and Wrap transformation. The paper based on the Wrap transformation, and the specific process is as follows

1) $f[n_1,n_2] \in R^2$ is decomposed by 2DFFT to get $\hat{f}[n_1,n_2](-n/2 \le n_1, n_2 \le n/2)$;

2) To all [j , ℓ], $\hat{f}[n_1,n_2]$ is used resampling or interpolation to get $\hat{f}[n_1, n_2 - n_1 \tan\theta_\ell]$;

3) multiply $\hat{f}$ by windows $\tilde{U}_j$ to get $\hat{f}_{j,l}[n_1,n_2] = \hat{f}[n_1, n_2 - n_1 \tan\theta_\ell]\tilde{U}_j[n_1,n_2]$;

4) $\hat{f}_{j,l}$ is used by 2DIFFT , get discrete Curvelet transform coefficient $c^D(j,\ell,k)$;

III. FUSION ALGORITHM PROCESS

The fusion rules and fusion operators are very important for image fusion. This paper use Curvelet transform to provide the detail of the image information, using the adaptive weighted to calculate high frequency factor weight and regional variance value to calculate low-frequency coefficients weight. Then in the wave domain through weighting to complete image fusion, image fusion has been assumed to match, the realization process is as follows.

After Image were multi-scale decomposed of by Curvelet , each coefficient in different frequencies and different decomposition levels have the corresponding

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coefficient of a group. Hypothesis two source images for A, B. The Curvelet decomposition coefficient respectively are $\left\{C_{j_0}^{A}(k_1,k_2),C_{j,l}^{A}(k_1,k_2)\right\}$ $\left\{C_{j_0}^{B}(k_1,k_2),C_{j,l}^{B}(k_1,k_2)\right\}$. The fusion image Curvelet coefficient are $\left\{C_{j_0}^{F}(k_1,k_2),C_{j,l}^{F}(k_1,k_2)\right\}$, where, $C_{j_0}(k_1,k_2)$ are low frequency coefficient, $C_{j,l}(k_1,k_2)$ the high frequency decomposition coefficient in different scales j, different direction l. To different characteristics of high and low frequency coefficient obtained by Curvelet decomposition, Fusion rules in this paper are as follows.

1) For the high frequency sub-band part, the design of the adaptive weighted fusion rules is follow.

First of all, high frequency coefficient $C_{j_l}^{A}(k_1,k_2)$, $C_{j_l}^{B}(k_1,k_2)$ of the two fused images respectively are separated into blocks, then to calculate corresponding to the neighborhood variance σ_A^2 and σ_B^2 of each block sized $m\times m$, with the assumption is greater than 1 the, weighted coefficient is as follow

$$K_{\max}=\begin{cases}\dfrac{\sigma_A}{\sqrt{\sigma_A^2+\sigma_B^2}} & \sigma_A^2>k\cdot\sigma_B^2\\ \dfrac{\sigma_B}{\sqrt{\sigma_A^2+\sigma_B^2}} & \sigma_B^2>k\cdot\sigma_B^2\\ 1 & others\end{cases}\qquad(4)$$

$$K_{\min}=\begin{cases}\dfrac{\sigma_B}{\sqrt{\sigma_A^2+\sigma_B^2}} & \sigma_A^2>k\cdot\sigma_B^2\\ \dfrac{\sigma_A}{\sqrt{\sigma_A^2+\sigma_B^2}} & \sigma_B^2>k\cdot\sigma_B^2\\ 0 & others\end{cases}\qquad(5)$$

According to the following formula, sub-block coefficient are obtained

$$C_{j,l,r}^{F}(k_1,k_2)=\begin{cases}K_{\max}\cdot C_{j,l,r}^{A}(k_1,k_2)+K_{\min}\cdot C_{j,l,r}^{B}(k_1,k_2) & \left|C_{j,l,r}^{A}(k_1,k_2)\right|>\left|C_{j,l,r}^{B}(k_1,k_2)\right|\\ K_{\max}\cdot C_{j,l,r}^{B}(k_1,k_2)+K_{\min}\cdot C_{j,l,r}^{A}(k_1,k_2) & \left|C_{j,l,r}^{A}(k_1,k_2)\right|\le\left|C_{j,l,r}^{B}(k_1,k_2)\right|\end{cases}\qquad(6)$$

Where, $C_{j,l,r}^{A}(k_1,k_2)$, $C_{j,l,r}^{B}(k_1,k_2)$ are respectively high frequency coefficient of sub-block corresponding to the position. r is sub-block serial number.

2) Using local deviation rule to calculate low-frequency coefficients weight.

$$C_{j_0}^{F}(k_1,k_2)=\begin{cases}C_{j_0}^{A}(k_1,k_2) & \sigma_{A,j_0}^2>\sigma_{B,j_0}^2\\ C_{j_0}^{B}(k_1,k_2) & \sigma_{A,j_0}^2<\sigma_{B,j_0}^2\end{cases}\qquad(7)$$

Repeat the above process, go through the whole block $C_{j,l}(k_1,k_2)$, Get high frequency coefficient of the decomposition layers. Finally use high and low frequency coefficient to reconstruction fusion image.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

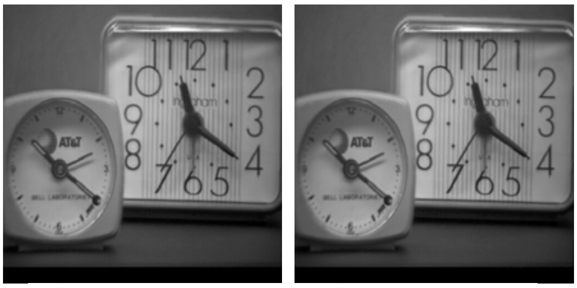
In order to verify the effect of the fusion algorithm, Experiments were done to a plurality of groups of multi-focus source image having different characteristics. The size of the experimental images are 256×256, In this paper, three more typical fusion algorithm were compared with. The first was Laplacian pyramid transform as the image of the multi-resolution decomposition tools; The second was wavelet transform as image multi-resolution decomposition tool. fusion rules in these two methods are the average in low-frequency part and a big modulus values in high-frequency coefficients[6]; the third method is based on Curvelet transform fusion algorithm in [7]. A set of experimental simulation effect images in two groups of experiment are shown as follow.


(a) Right focused image


(b) Left focused image


(c)Laplacian fusion algorithm

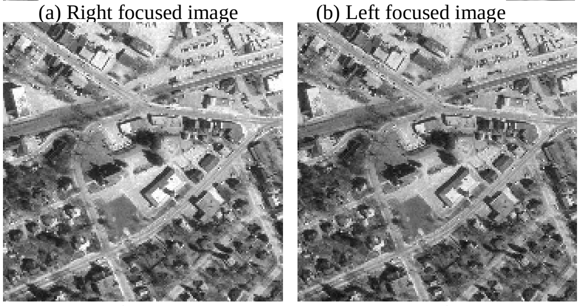

(d) wavelet transform algorithm



(e) fusion algorithm in [7] (f) algorithm in the paper

Figure 1. Different fusion methods effect pictures (1)

(a) Right focused image (b) Left focused image



(c)Laplacian fusion algorithm (d) wavelet transform algorithm

(e) fusion algorithm in [7] (f) algorithm in the paper

Figure 2. Different fusion methods effect pictures (2)

As can be seen from the above fusion effect pictures. Laplacian pyramid image fusion algorithm appears certain degree of fuzzy, ghosting and distortions in some places. Fusion algorithm using wavelet transform and Curvelet transform can get a good fusion result. The goals are relatively clear image. By further comparison, the fused image using wavelet transform has subtle ghosting. Curvelet transform fusion images effectively eliminate this phenomenon to obtain sharper images, especially on thethe more complex part of the texture. In addition to the subjective evaluation of the fused image, the three indicators[8] were used including information entropy (entropy), the average gradient (average gradient) and the mean square error (MSE) to conduct an objective evaluation of the quality of the fused image. Table 1 and 2 show the objective evaluation of the above two groups of experiment effect in the different algorithms comparison.

TABLE I. FUSION PERFORMANCE EVALUATION OF THE DIFFERENT APPROACHES IN EXPERIMENT 1.

fusion algorithm	comentropy	Average gradient	MSE
Laplacian algorithm	6.9837	25.2878	0.9983
wavelet transform algorithm	7.0546	25.4525	0.9988
fusion algorithm in [7]	7.0985	27.3926	0.9986
algorithm in the paper	7.1354	27.5237	0.9985

TABLE II. FUSION PERFORMANCE EVALUATION OF THE DIFFERENT APPROACHES IN EXPERIMENT 2.

fusion algorithm	comentropy	Average gradient	MSE
Laplacian algorithm	7.6472	18.7374	5.0734
wavelet transform algorithm	7.6485	18.7805	3.9665
fusion algorithm in [7]	7.7044	18.9637	1.9948
algorithm in the paper	7.7126	19.1094	0.8318

Above results presented image fusion algorithm based on Curvelet transform can obtain the largest information entropy and average gradient and the minimum mean square error. Therefore, our experiments show that compared with some traditional algorithms, this algorithm has better performance. edge detail in the original image information is saved the best overall performance is superior to other methods. It is mainly due to the different multi-resolution decomposition tools and different fusion rules.

V. CONCLUSION

Curvelet transform is able to represent smooth and edge parts of image with sparsity which can provide more image information than wavelet transform. Using it to multi-focus image fusion in this paper, the edge detail information of the original image of are well preserved. The experiments show that the curvelet transform as a multi-scale geometric analysis tool, there is a good prospect in the field of remote sensing image fusion.

REFERENCES

[1] Ranchin T, Wald L. The wavelet transform for the analysis of remotely sensed images[J].International Journal of Remote Sensing, 1993, 14(3): 615-619.

[2] E. J. Candès, “Harmonic analysis of neural networks,” Appl. Comput. Harmon. Anal., vol. 6, pp. 197–218, 1999.

[3] J. L. Starck, E. J. Candès, and D. L. Donoho, “The curvelet transform for image denosing,” IEEE Trans. Image Process., vol. 11, no. 6, pp. 670–684, Jun. 2002.

[4] Donoho D.L. Orthonormal ridgelets and linear singularities [R]. Tech. Report, Department of Statistics, Stanford University, 1998.

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[5] Candès E J, Demanet L, Donoho D L, et al. Fast discrete curvelet transforms. Appied and Computational Mathe ematics, Califormia Institute of Technology, 2005:1-43.

[6] Qang Zhan xia, et al. Remote sensing image fusion based on wavelet transform local variance [J]. Huazhong University of Science and Technology (Natural Science), 2003, 31(6): 89-91.

[7] L. Alparone, S. Baronti, A. Garzelli, F. Nencini. Remote sensing image fusion using the curvelet transforms. International Journal on Information Fusion, Elsevier, 2007, 8(2):143-15.

[8] Xiao Gang, Jing Zhong liang, Wu Jian min, Liu Congyi. Synthetically evaluation system for multi-source image fusion and experiment analysis[J]. Journal of Shanghai Jiaotong University, 2006, 11(3):263-270.

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