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An Image Fusion Algorithm Based on Wavelet Transform and Fourier Measurement Matrix

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Abstract. *The traditional image fusion algorithms carry out fusion based on the information of all the pixels in the original images. This leads to the problem of high time and space complexity for the fusion algorithms. To solve this problem, this paper proposes an improved image fusion algorithm based on wavelet transform and Fourier random measurement matrix. The proposed fusion algorithm only acts on a small amount of data after the compressive sensing sampling. The image fusion is completed in the compressive sensing domain. The fused image is reconstructed by the orthogonal matching tracking algorithm. The experimental results show that this proposed image fusion algorithm based on wavelet transform and Fourier random measurement matrix has good performance.*
Keywords: Image Fusion, Wavelet Transform, Fourier Random Measurement Matrix, Orthogonal Matching Tracking Algorithm

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1. **Introduction.** At present, there are three levels of image fusion: pixel-level fusion, feature-level fusion and decision-level fusion. The feature-level fusion first extracts the features of each original image. After the feature extractions on the texture, edge, corner, line and specific area of an image, the image fusion is completed with the extracted feature parameters. The decision-level fusion first extracts the features of original images. Then, the image fusion is completed according to the understandings of the extracted image features. The pixel-level fusion algorithm directly carries out the fusion process on image pixels. Therefore, the time complexity and space complexity are higher. The compressive sensing theory breaks through the requirements of traditional Nyquist sampling theorem, reduces the sampling data amount. This theory compresses the image data while acquiring the image. It provides new image acquisition and processing framework, and provides new research ideas for the image fusion with large data amount[1−4].

After the match of the to-be-fused images, the image fusion algorithm, which is based on compressive sensing theory, obtains the measured values of the two images by conducting dimensional reduction transform on the two images using the designed Fourier random measurement matrix. Then, the fusion of the measured values is carried out according to the fusion rule in the compressive sensing domain. Finally, the fused image is reconstructed according to the reconstruction algorithm of compressive sensing theory.

2. An Image Fusion Method Based On Wavelet Transform and Fourier Measurement Matrix.

2.1. The Measurement and Fusion of Image Dimensional Reduction. Firstly, the sparse representation of the original image is obtained with the wavelet transform. Then, the dimensional reduction measurement is carried out using Fourier random measurement matrix, and the image fusion is completed in the compressive sensing domain. The image fusion algorithm based on wavelet transform and Fourier random measurement matrix, and its implementation steps are shown as follows:

Step 1: Carry out accurate matching for two images F1 and F2.

Step 2: Carry out sparse transformation on image F1 and image F2 using wavelet transform. For an image F ($N \times N$, N=2K):

$$F(x,y) = \begin{bmatrix} f_{0.0} & f_{0.1} & \cdots & f_{0.2K-1} \\ f_{1.0} & f_{1.1} & \cdots & f_{1.2K-1} \\ \cdots & \cdots & \cdots & \cdots \\ f_{2k-1.0} & f_{2K-1.1} & \cdots & f_{2K-1.2K-1} \end{bmatrix}$$

The wavelet sparse transformation of an image is achieved with Mallat algorithm. It can be calculated with Equations from (1) to (4) [5,12].

$$LL_{x,y} = \frac{1}{4}\sum_{k_1,k_2=0}^{l} p_{k_1}p_{k_2}i_{k_1+2x,k_2+2y} = \frac{1}{4}(i_{2x,2y} + i_{2x,2y+1} + i_{2x+1,y} + i_{2x+1,2y+1})(1)$$

$$LH_{x,y} = \frac{1}{4}\sum_{q_1,k_2=0}^{l} p_{k_1}q_{k_2}i_{k_1+2x,k_2+2y} = \frac{1}{4}(i_{2x,2y} - i_{2x,2y+1} + i_{2x+1,y} - i_{2x+1,2y+1})(2)$$

$$HL_{x,y} = \frac{1}{4}\sum_{k_1,k_2=0}^{l} q_{k_1}p_{k_2}i_{k_1+2x,k_2+2y} = \frac{1}{4}(i_{2x,2y} + i_{2x,2y+1} - i_{2x+1,y} - i_{2x+1,2y+1})(3)$$

$$HH_{x,y} = \frac{1}{4}\sum_{k_1,k_2=0}^{l} q_{k_1}q_{k_2}i_{k_1+2x,k_2+2y} = \frac{1}{4}(i_{2x,2y} - i_{2x,2y+1} - i_{2x+1,y} + i_{2x+1,2y+1})(4)$$

Step 3: Conduct dimensional reduction measurement on image F1 and image F2 with Fourier random measurement matrix. The elements in the Fourier matrix are shown in Equation (5) [6,12].

$$F_{j,k} = \frac{1}{\sqrt{N}}e^{i2\pi jk/N}(5)$$

Carry out dimensional reduction measurement on images,$X = \Phi F = \Phi\psi\mu = \Theta\mu$, and the measured values X_1,$X_2$of the images are obtained.

Step 4: Carry out coefficients fusion on measured valuesX_1,X_2.

To achieve better fusion performance, not only the fusion of the corresponding pixels on the original images should be considered during the image fusion, but also the local regions of the corresponding pixels should be taken into account. The variance $Dev(X)$ and entropy$E(X)$ of the local fusion region are used as the fusion parameters[7]. The values of variance $Dev(X)$ and entropy $E(X)$can be calculated according to Equations (6) and (7).

$$Dev(X) = \frac{1}{D_1 \times D_2}\sum_{0}^{D_1-1}\sum_{0}^{D_2-1}(G(X_{i,j}) - \overline{G}(X))^2(6)$$

$$E(X) = -\sum_{i=0}^{L-1} P_i \log(P_i) (7)$$

In Equation (6), $Dev(X)$represents the variance (D1, D2 are small integers) of region $(D_1 \times D_2)X$. $G(X_{i,j})$ represents the measured value of (m, n) in the region X. $\overline{G}(X)$ represents the average value of the measured values for the region X. In Equation (7), $E(X)$ represents the entropy, P_i represents the ratio of the pixels with gray value of i in the region X, and L is the gray scale. During the fusion of the measured values, the measured value of the central pixel of the region with lager variance$Dev(X)$ and entropy$E(X)$ is taken as the value of the fusion result.

2.2. **Image reconstruction.** In this paper, the orthogonally matching tracking algorithm (OMP) [8]is used for image reconstruction with the fused measurement values.

The implementation steps are as follows[9,10,11]:

Step 1: ϕrepresents the Fourier random measurement matrix, X denotes the observation vector, K is the sparse degree, $r$is the residual. The residual is initialized to $r^0 = X$, and the number of iterations is initialized to zero.

Step 2: Y_0 is used to represent the sparse solution of reconstruction, I denotes the index set, I = E.

Step 3: Calculate the correlation coefficient μ ,$u = \phi^T r$, and calculate the maximum value of μ in the meantime. Then, add the corresponding index value of the maximum value in μ to the index set J.

Step 4: Add the corresponding elements of the index values in J to the set I. And set the corresponding elements in the Fourier random measurement matrix ϕ to 0.

Step 5: Solve the support set ϕ_I , $I = U \cup I$.

Step 6: Solve the approximate solution Y by using the least squares method, $Y = (\Phi_I^T \Phi_I)^{-1} \Phi_I X$.

Step 7: Calculate the residual ,$r = X - \Phi_I Y$.

Step 8: Judge the iteration termination condition. If $|I| < 2K$ and also $nor(m) > \delta$, or $||r^n - r^{n-1}|| \leq 10^-6$, then the number of iterations is incremented by 1, and then go to step 3 to continue, otherwise the iteration is terminated.

3. **Evaluation Parameters for Image Fusion.** Because image fusion is lack of standard image as reference image, the fusion result image cannot be compared with the reference image. Therefore, the traditional image processing performance evaluation parameters such as mean squared error (MSE), peak signal to noise ratio (PSNR) cannot be used for the objective evaluation of fusion experiment performance. This paper selected currently commonly used evaluation methods that do not need reference images to analyze the experimental results, which mainly includes spectral angle mapper (SAM) and improved SAM(ISAM).

The SAM is defined as follows[13,14]:

$$SAM_U V = across \frac{\sum_i u_i v_i}{\sqrt{\sum_i u_i^2} \sqrt{\sum_i v_i^2}} (8)$$

The ISAM is defined as follows[15]:

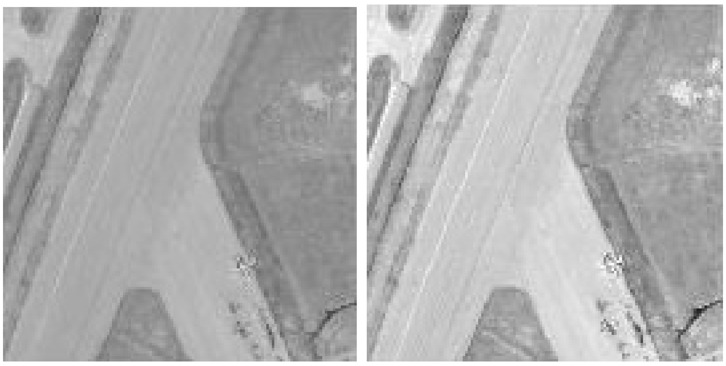
$$ISAM_U V = across \left(\frac{2 \sum_i u_i v_i}{\sqrt{\sum_i u_i^2} \sqrt{\sum_i v_i^2}} \right) (9)$$

Where, and represent the vectors in the original images U and V , where, and represent the mean values of U and V,$U = \{u, u, ..., u\} V = \{v, v, ..., v\}$, $u \neq v$.

4. **Experimental Analysis.** In order to verify the effectiveness of the fusion algorithm, the image fusion method based on wavelet transform and Fourier measurement matrix, principal component analysis method, and pyramid method are used to carry out fusion experimental analysis on both full color image and visible light image. The fusion results are shown in Fig. 1.

Fig. 1 (a) is an infrared imaging image F1. Fig. 1 (b) is a visible light image F2, the image pixel size is 256 * 256. Fig. 1 (c) is the fusion result image based on principal component analysis. Fig. 1 (d) is the fusion result image based on pyramid method. Fig. 1(e) is the obtained fusion result image by the fusion algorithm based on wavelet transform and Fourier measurement matrix.

(a) Infrared image F1 (b) Image F2 from visible light imaging



(c) The fusion result image based on the principal component analysis

(d) The fusion result image based on pyramid method

(e) The obtained fusion result image by the fusion algorithm based on wavelet transform and Fourier measurement matrix

Fig. 1 The fusion results for both infrared image and visible light image

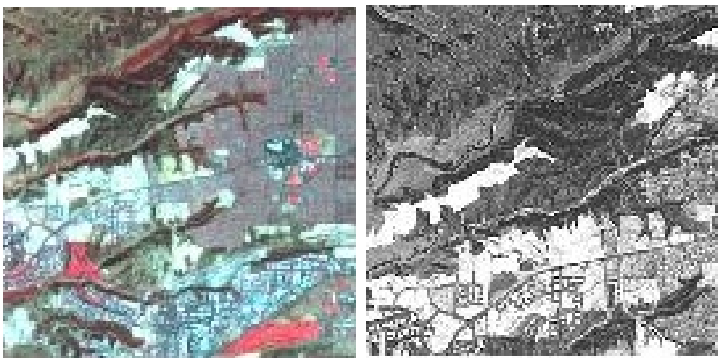
The information entropy, average gradient, mutual information, SAM and ISAM are selected as the evaluation parameters to compare and analysis the experimental results. The ‘I’, ‘V’ and ‘F’ represent the infrared, visible light and fused images, respectively. The evaluation parameters of the obtained fusion result image using three fusion algorithms are shown in Table 1.

Table 1 **The evaluation parameters of fusion quality for both infrared image and visible light remote sensing image**

Fusion method	Information entropy	Average gradient	Mutual information	SAM_{IF}	$ISAM_{IF}$	SAM_{VF}	$ISAM_{VF}$	Time consumption(s)
Principal component analysis	6.923	0.023	1.867	0.2946	0.465	0.152	0.177	30
Pyramid method	7.12	0.0341	1.835	0.257	0.349	0.208	0.212	94
A Fusion Method Based on Wavelet Transform and Fourier Measurement Matrix	6.528	0.016	1.73	0.269	0.359	0.147	0.155	55

This paper carries out fusion experiments analysis on multi-spectral image and full color image. Fig. 2 (a) is a multi-spectral image, Fig. 2 (b) is a full-color image, and the image pixel size is 256 * 256. Remote sensing image fusion method based on wavelet transform and Fourier measurement matrix, principal component analysis method, and pyramid method are used to carry out fusion experimental analysis on both the full color image and multi-spectral image. The fusion results are shown in Fig. 2.

The 'M', 'P' and 'F' are used to represent multi-spectral, full color and fused images, respectively. The objective evaluation parameters of the three fusion algorithms are shown in Table 2.



(a) Multi-spectral image F1 (b) Full color image F2

(c) The fusion result image based on principal component analysis

(d) The fusion result image based on pyramid method

(e) The fusion result image of remote sensing image fusion method based on wavelet transform and Fourier measurement matrix

Fig. 2 The fusion results of full-color image and multi-spectral image

Table 2 **The quality evaluation table of fused images for both multi-spectral and full-color remote sensing**

Fusion method	Information entropy	Average gradient	Mutual information	SAM_{MF}	$ISAM_{MF}$	SAM_{PF}	$ISAM_{PF}$	Time consumption(s)
Principal component analysis	20.723	64.563	6.874	0.335	0.643	0.129	0.397	25
Pyramid method	19.212	74.521	7.117	0.155	0.560	0.193	0.386	90
A Fusion Method Based on Wavelet Transform and Fourier Measurement Matrix	20.852	47.203	6.751	0.388	0.562	0.325	0.389	43

The experimental results show that the improved image fusion algorithm based on wavelet transform and Fourier measurement matrix achieved good evaluation parameters in multi-source image fusion experiments. In the fusion experiments of infrared imaging image with visible light image, and the fusion experiments of multi-spectral image with full-color image, the evaluation parameters of average gradient, mutual information, SAM and ISAM have achieved good experimental results. These experiments show that the improved image fusion algorithm based on wavelet transform and Fourier measurement matrix only acts on a small amount of measurement data after compressive sensing sampling, which greatly reduces the number of pixels involved in the fusion and decrease the time and space complexity of fusion. And the image fusion performance is better.

5. **Conclusions.** This paper applies compressive sensing theory to the image fusion process. An improved image fusion algorithm based on wavelet transform and Fourier measurement matrix is proposed. This proposed algorithm overcomes the problems of large data amount and high time complexity that exist in traditional image fusion algorithms. It only acts on a small amount of data after compressive sensing sampling. The image

fusion is completed in the compressive sensing domain. The fused data is reconstructed by the reconstruction algorithm of compressive sensing theory to obtain the fusion result image. This algorithm has achieved good experimental results.

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REFERENCES

[1] S. Q. Liu, M. Z. Shi, Z. H. Zhu, J. Zhao, Image fusion based on complex-shearlet domain with guided filtering, Multidimensional Systems and Signal Processing, vol. 28 , no. 1, pp.207-224, 2017.

[2] N. R. Amini, E. Fatemizadeh, H. Behnam. MRI-PET image fusion based on NSCT transform using local energy and local variance fusion rules. Journal of Medical Engineering & Technology, 2014, 38, no. 4, pp.211-219.

[3] K .K. Sharma, M. Sharma, Image fusion based on image decomposition using self-fractional Fourier functions, Signal, Image and Video Processing, 2014, vol. 8 , no. 7), pp.1335-1344.

[4] Y. Lu, F. X. Wang, X. Y. Luo, F.Liu, Novel infrared and visible image fusion method based on independent component analysis, Frontiers of Computer Science, 2014, vol. 8 , no. 2), pp.243-254.

[5] E. J. Candes and D. L. Donoho. Curvelets - a surprisingly effective non-adaptive representation for objects with edges. *Technical report, Stanford University,* 1999.

[6] Z. Xie, Research on sparse reconstruction algorithm of compressive sensing *[PhD thesis] Nanjing: Nanjing University of Aeronautics and Astronautics*, 2012.5.

[7] Z. Qiang, The fusion and application of remote sensing image, *[PhD thesis], Wuhan: Huazhong University of Science and Technology,* 2005, pp. 36-44.

[8] C. Deng, Research on image sparse representation theory and its applications *[PhD thesis], Wuhan: Huazhong University of Science and Technology*, 2008.04.

[9] Y. Yang, Image fusion based on non-sampling Contourlet [PhD thesis], *Changchun: Graduate School of Chinese Academy of Sciences*, 2012, pp. 113-129.

[10] Peng Ke, Cheolkon Jung, Ying Fang, Perceptual multi-exposure image fusion with overall image quality index and local saturation, *Multimedia Systems, vol. 23 , no. 2), pp.239-250, 2017.*

[11] M. Ahron, Elad M, Bruckstein A M.K-SVD: An Algorithm for Designing Overcomplete Dictionaries for Sparse Representation. *IEEE Trans.on Image Processing*, vol. 15, no. 11 , pp. 4311-4322, 2006.

[12] Q. Yang, H. J. Wang, X. q. Luo, Research on Remote Sensing Image Fusion Algorithm Based on Compressed Sensing, *International Journal of Hybrid Information Technology*, vol. 8, no. 5 , pp. 283-292, 2015.

[13] W. Li, C. C. Lin, J. S. Pan, Novel Image Authentication Scheme with Fine Image Quality for BTC-based Compressed Images, *Multimedia Tools and Applications*, vol. 75, no. 8., pp. 4771-4793, 2016.

[14] Y. Tong, J. Chen ,Compressive sensing image fusion in heterogeneous sensor networks based on shear let and wavelet transform, *EURASIP Journal on Wireless Communications and Networking*, 2017, vol. 2017 , no. 1, pp. 1-5.

[15] Q. X. Feng, Xi. J. Zhu and J. S. Pan, Novel Classification Rule of Two-Phase Test Sample Sparse Representation, *OPTIK-International Journal for Light and Electron Optics*, vol. 125, issue 19, pp. 5825-5832, 2014.