Medical Image Fusion in Compressed Sensing Based on Non-subsampled Contourlet Transform*

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***Abstract*—In order to get better results and faster speed on medical image fusion, a method based on non-subsampled contourlet transform in compressed sensing was proposed. Because of the large sparsity and sharp contrast between the black and the white of medical images, the energy and average gradient were utilized to design the fusion rules to fuse the low-frequency components and the high-frequency components respectively. The image entropy, relative quality, average gradient, standard deviation and spatial frequency were used to evaluate the fusion results objectively. Experiments show that under the premise of maintaining a certain reconstruction quality the sample rates and calculation amounts are lower; the convergence can be sped up and the fusion results can be improved.**

Keywords—Medical Images; NSCT; CS; Image Fusion

I. INTRODUCTION

With the development of medical technology, medical images in medical diagnostics are playing an increasingly important role. Multiple-modality medical image information obtained from different medical imaging equipment can describe more morphological and functional information of same human organs which can't be acquired in single medical image. Simultaneously, the information in single medical image is different and complementary, such as the CT images are very clear on bone imaging while the contrast of soft tissue is relatively low; MRI images are better to show the soft tissue and the vascular. In order to provide the more valuable information and more accurate reference to medical diagnosis and cure, the medical images fusion technology is used to integrate the different information which comes from different medical imaging equipment in [1-3].

Recently, the image fusion algorithms based on multi-scale decomposition have been widely applied in medical image fusion, and the non-subsampled contourlet transform is one of them. On the basis of contourlet, NSCT is composed of non-subsampled directional filters, and it has translation invariance. NSCT can remove the artifacts in the course of image fusion caused by Gibbs' effects. Although the algorithm based on NSCT can improve the fusion results, it still has a higher redundancy, calculation amounts and the computational complexity. Due to the improving resolution of the medical images, the above parameters will be increasing greatly and the running time will be cost too much. Aiming at these problems, a fusion method in compressed sensing based on non-subsampled contourlet transform is proposed. Under the premise of the maintaining a certain reconstruction quality, the presented algorithm can reduce the calculation amounts and the sample rates, speed up the convergence and improve the results.

Project of Jilin Province Science and Technology Department (No. 20102109)

II. BACKGROUND

A. Compressed Sensing--CS

The CS theory was developed by Candes, Romberg, Tao and Donoho in [4-6]. CS theory shows that if a signal can be represented sparsely, with far less than the number of the observations required by the Nyquist theorem on minimum sampling rate the original signal can be accurately reconstructed. The process on CS theory concludes 3 parts: signal sparse representations, signal measurements and signal reconstruction. The system diagram of CS theory is shown in Fig.1.

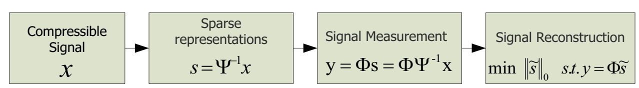


Fig.1 The system diagram of CS theory

The four main implementation steps are as follows:

- Represent the original signal x sparsely in a certain domain Ψ.

$$x=\Psi S \qquad or \qquad x=\sum_{i=1}^{N} S_i \Psi_i \tag{1}$$

Where, $\Psi=[\Psi_1,\Psi_2,\cdots,\Psi_N]$, S is sparse he representation of x.

- Design a measurement matrix $\Phi(M<<N)$ unrelated to Ψ to accomplish the linear transformation of S. The measurement result is $\Phi(M<<N)$.

$$\mathrm{y}=\Phi \mathrm{s}=\Phi\Psi^{-1}\mathrm{x} \tag{2}$$

- Calculate the sparse signal $\tilde{s}$ according to y,Ψ,Φ.

$$\min\|\tilde{s}\|_0 \quad s.t. \quad y=\Phi\tilde{s} \tag{3}$$

- Reconstruct the original signal x.

$$\tilde{x}=\Psi\tilde{s} \tag{4}$$

978-0-7695-5159-3/13 $31.00 © 2013 IEEE
DOI 10.1109/MSN.2013.92

B. Non-subsampled Contourlet Transform--NSCT

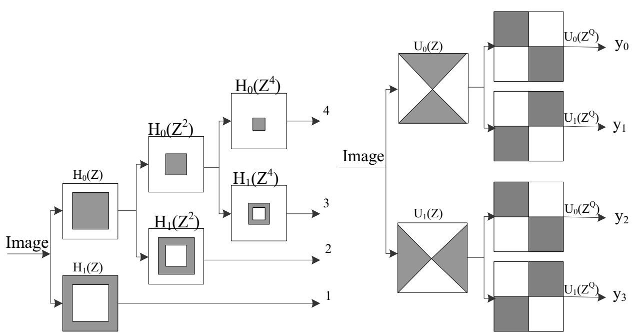
NSCT is comprised of NSPFB (non-subsampled pyramid filter bank) and NSDFB (non-subsampled directional filter bank) in [7-8]. NSPFB is mainly composed of decomposition filter and reconstruction filter, which are satisfied the formula (5). The decomposition structure is shown in Fig.2 (a).

$$H_0(z)G_0(z)+H_1(z)G_1(z)=1 \tag{5}$$

Where $G_0(z)$ is the lowpass and $G_1(z)$ is the high pass synthesis filters. $H_0(z)$ denote the lowpass analysis filter and $H_1(z)$ is the corresponding high pass filter at the first stage, $H_1(z)=1-H_0(z)$.

NSDFB is mainly composed of decomposition filter $\{U_0(z),U_1(z)\}$ and reconstruction filter $\{V_0(z),V_1(z)\}$, which are satisfied the formula (6). The decomposition structure is shown in Fig.2 (b).

$$U_0(z)V_0(z)+U_1(z)V_1(z)=1 \tag{6}$$



(a) NSFB Structure in NSCT (b) NSDFB Structure in NSCT

Fig.2 Non-subsampled Contourlet Transform

III. PROPOSED FUSION ALGORITHM

The medical images have larger sparsity, and the effective detail information of the images can be extracted by using NSCT. The high-frequency components after the decomposition could be compressed greatly. By employing the CS technology in the image fusion process, the calculation amounts could be reduced and the fusion speed could be quickened. It is the basic idea that the algorithm is presented.

A. Diagram of Fusion Scheme

The block diagram of the medical image fusion in CS based on NCST is shown in Fig.3. In Fig.3, LFC represents the low-frequency components; HFC represents the high-frequency components.

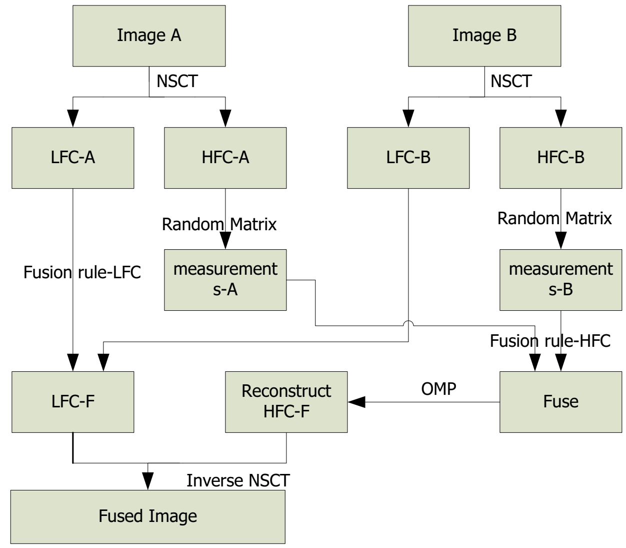


Fig.3 The diagram of fusion scheme

The various implementation steps involved in the proposed fusion algorithm are as follows:

- Decompose the CT image and MRI image using Non-subsampled Transform into low-frequency and high-frequency components.
- Fuse the low-frequency components based on the weighted fusion guided by regional energy and gradient.
- Apply the CS technology in the sparse high-frequency components. The high-frequency components are observed by using random matrix. And the measurements of the high-frequency components are fused by utilizing the fusion rule.
- Reconstruct the high-frequency components by employing the reconstruction algorithm-orthogonal matching pursuit (OMP).
- Apply inverse NSCT to obtain the fused image.

B. The Selection of Fusion Rules

The coefficient of low frequency represents contour information, and which is the approximation of source images and don’t have sparsity. The coefficient of high frequency represents detail information, and which has large sparsity. In the paper, the coefficient of low frequency is fused based on weighted regional energy, and the coefficient of high frequency is fused based on weighted gradient and energy.

- Fusion rule of low-frequency components

The regional energy E, gradient $Grad$, window function v are given by:

$$v=\frac{1}{8}\begin{bmatrix}0&1&0\\1&4&1\\0&1&0\end{bmatrix} \tag{7}$$

$$E(i,j)=\sum_{k=-n'}^{n'}\sum_{r=-n'}^{n'} f^2(i+k,j+r)v(i+k,j+r) \tag{8}$$

$$Grad(i,j)=\frac{1}{n\times n}\sum_{k=-n'}^{n'}\sum_{r=-n'}^{n'}\sqrt{\frac{\left(\frac{\partial f(i+k,j+r)}{\partial x}\right)^2+\left(\frac{\partial f(i+k,j+r)}{\partial y}\right)^2}{2}} \tag{9}$$

Where, n is the number of the row v , n' is integers of $n/2$ downwardly.

A_L and B_L are the coefficient of low frequency of image A and image B, the regional energy is E_{LA} and E_{LB} respectively. The weight coefficient K_{LA}, K_{LB} is given by:

$$\begin{cases} K_{LA}=E_{LA}/(E_{LA}+E_{LB}) \\ K_{LB}=E_{LB}/(E_{LA}+E_{LB}) \end{cases} \tag{10}$$

The coefficient of low frequency C_L after fusion is given by:

$$C_L(i,j)=K_{LA}*A_L(i,j)+K_{LB}*B_L(i,j) \tag{11}$$

- Fusion rule of high-frequency components

A_H and B_H are the coefficient of high frequency of image A and image B. $Grad_{HA}$ and $Grad_{HB}$ are the gradient. The regional energy is E_{HA} and E_{HB} respectively. The weight coefficient K_{HA}, K_{HB} is given by:

$$\begin{cases} K_{HA}=Grad_{HA}/(Grad_{HA}+Grad_{HB}) \\ K_{HB}=Grad_{HB}/(Grad_{HA}+Grad_{HB}) \end{cases} \tag{12}$$

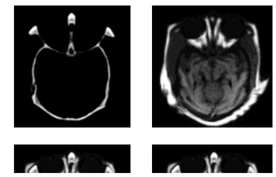
The coefficient of high frequency C_H after fusion is given by:

$$C_H(i,j)=\begin{cases} A_H(i,j), & E_{HA}>E_{HB}\ and\ Grad_{HA}>Grad_{HB} \\ B_H(i,j), & E_{HA}<E_{HB}\ and\ Grad_{HA}<Grad_{HB} \\ K_{HA}*A_H(i,j)+K_{HB}*B_H(i,j), & \text{else} \end{cases} \tag{13}$$

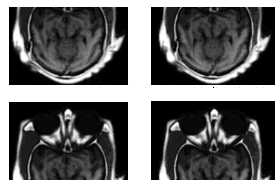
IV. Experimental Results And Discussion

In order to verify the effectiveness and the validity of the proposed algorithm, the two sets of medical images with the size of 256×256 are chosen to conduct the experiments. The random matrix in [9-10] is selected as the measurement matrix, and the orthogonal matching pursuit (OMP) in [11-13] is chosen as the reconstruct algorithm. In this paper, the fusion algorithm based on traditional wavelet transform (WT), the fusion algorithm based on contourlet transform (CT), the fusion algorithm based on NSCT and the proposed fusion algorithm are compared. The fusion results are as seen in Fig.4 and Fig.5. The fusion results with different sample rates are shown in Fig.6 and Fig.7. The sample rate is 5%, 10%, 30%, 50% respectively.

As shown in Fig.4-Fig.7, from a subjective point of view the proposed algorithm can get the better fusion results, and the fused image is more clear and accurate. The quality of the fused image could be better.



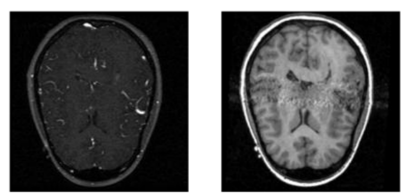
(a) Image A (b) Image B



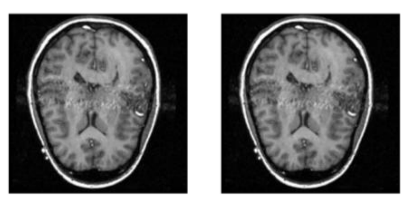
(c) Wavelet fusion (d) Contourlet fusion

(e) NCST fusion (f) Proposed method

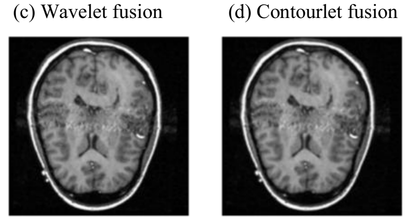
Fig.4 Comparison results of fusion methods in first set image



(a) Image A (b) Image B

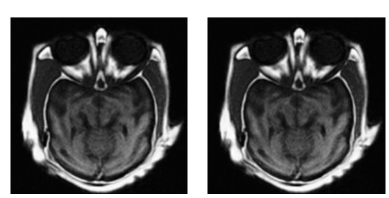


(c) Wavelet fusion (d) Contourlet fusion

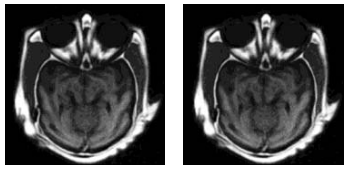


(e) NCST fusion (f) Proposed method

Fig.5 Comparison results of fusion methods in second set image

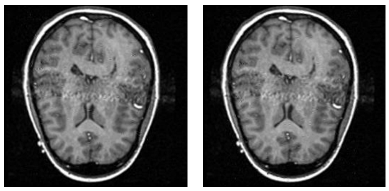


(a) Sample rate 5% (b) Sample rate 10%

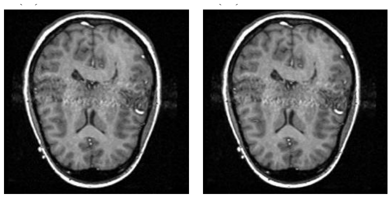


(c) Sample rate 30% (d) Sample rate 50%

Fig.6 Fusion results with different sample rates in first set image



(a) Sample rate 5% (b) Sample rate 10%



(c) Sample rate 30% (d) Sample rate 50%

Fig.7 Fusion results with different sample rates in second set image

The image entropy (H), relative quality (Qabf), average gradient (AvGra), standard deviation (StaD) and spatial frequency (SF) were used to evaluate the fusion results objectively. The comparison results of 4 methods are shown in TABLEI and TABLEII.

TABLE I. PERFORMANCE EVALUATION OF VARIOUS METHODS FOR FIRST SET OF MEDICAL IMAGE

	H	Q(abf)	AvGra	StaD	SF	Time(s)
WT Fusion	6.80	7.96	61.45	0.83	20.54	1.09
CT Fusion	6.86	7.52	61.33	0.77	19.05	3.45
NSCT Fusion	6.85	7.31	61.20	0.73	17.57	3.18
CS-NSCT (5%)	6.87	7.22	61.03	0.75	17.72	0.595
CS-NSCT (10%)	6.89	7.35	61.05	0.74	17.89	0.725
CS-NSCT (30%)	6.89	7.34	61.10	0.75	18.19	1.26
CS-NSCT (50%)	6.90	7.45	61.13	0.75	18.28	1.51

TABLE II. PERFORMANCE EVALUATION OF VARIOUS METHODS FOR SECOND SET OF MEDICAL IMAGE

	H	Q(abf)	AvGra	StaD	SF	Time(s)
WT Fusion	6.39	10.72	68.78	0.27	27.40	1.07
CT Fusion	6.53	10.47	68.77	0.62	26.82	1.51
NSCT Fusion	6.55	10.37	68.56	0.63	26.71	4.18
CS-NSCT (5%)	6.66	9.33	67.96	0.58	23.09	0.60
CS-NSCT (10%)	6.68	9.86	68.03	0.59	23.82	0.73
CS-NSCT (30%)	6.69	10.23	68.20	0.61	24.95	1.12
CS-NSCT (50%)	6.68	10.08	68.31	0.60	25.41	1.31

As shown in TABLE I and TABLE II, the fusion results applied the CS technology is better than the traditional fusion method based on NSCT. The presented algorithm in the paper has higher image entropy. When the sample rate is 30%, the running time has been remarkably reduced while the rest parameters have a near level.

V. CONCLUSION

The medical images have larger sparsity, and the effective detail information of the images can be acquired by using NSCT. The CS technology applied in the image fusion can reduce the calculation amounts and quicken the fusion speed. The experimental results show that the fusion algorithm in CS based on NSCT has better fusion results and lower computational complexity, and the different information of different human organs can be synthesized and displayed in one picture.

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