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Medical Image Fusion in NSCT Domain Combining with Compressive Sensing

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Abstract

In recent years, with the development of compressive sensing (CS) theory, it has been widely applied to each field including image fusion, and obtained better fusion effect. And CS can reduce dimensions and the amount of data characteristics as well as the large amount and high computation complex. Therefore, this paper proposes a novel medical image fusion method based on compressive sensing theory in non-subsampled contourlet transform (NSCT) domain. First, NSCT transform is applied to the source images, and the coefficients in low frequency subband are fused by mean rules. For high frequency subband, CS is applied and the coefficients are fused by neighborhood-energy-MAX (NE-MAX) rule, then inverse CS is used to get fused coefficients. Finally, inverse NSCT is applied to get the reconstructed image. The experimental results show that the fusion algorithm proposed in this paper is superior to fusion method based on WT-MAX and CS-MAX、CS-MEAN.

Keywords: *image fusion; CS; NSCT; neighborhood energy*

1. Introduction

Image fusion is an important branch of information fusion and research focus. Its purpose is to extract and integrate multiple source image information, eliminate redundancies and contradictions that may exist between diverse information, to obtain the desired objectives more clearly accurate, more comprehensive and reliable description for further analysis and understanding for people. The advantages of so many aspects make image fusion receive fully understanding of the potential in medicine, remote sensing, computer vision, weather prediction and military target recognition, especially in the computer vision.

In recent thirty years, a large number of researches on image fusion technology are taken by scholars at home and abroad. However, because medicine image fusion related equipment prices are very high and fusion process's time is long, research on image fusion is still not mature and the system is not perfect at home. Actual image fusion methods mostly proceed in transform domain. Non-subsampled contourlet transform (NSCT), not only has multi scale and local characteristics in time domain, but also the sampling process is non-sampling use, so it also has translation invariance, and the image may be sparse represented [3, 4].

Candes and Donoho put forward formally compressive sensing on the basis of related researches in 2006. It pointed out that, if a signal is sparse, then we can use a few random sampling point that much lower than Nyquist frequency to perfectly reconstruct the original signal. In consideration of large amounts of the original image fusion method, but CS theory can be underway the data's dimensionality reduction well. Wan proposed image fusion based max value rules combing with CS theory. He gave the method which used mean rule for image fusion after CS transform.

Therefore, this article will use NSCT transform combining CS theory for medical image fusion. In the NSCT transform domain using the mean method for low frequency coefficients fusion, then CS is applied for high-frequency coefficients, and choose the max energy of neighborhood for coefficients fusion. Then INSCT is used to obtain fused image. Simulation results show that, the proposed method in NSCT domain combing with CS has made a better fusion effect on both visual effects and objective evaluation.

2. Theory of NSCT

Contourlet Transform (CT) is one of the best kind of multi-scale image analysis method analysis, its flexible multi-directional filtering capability can capture the intrinsic geometry of the image, while NSCT is a multiscale computational framework of discrete direction of the image which put forward on the theory of CT.

NSCT can be considered to enhance the technology of CT, NSCT uses multi-directional decomposition and multi-scale decomposition for images. CT of the input signal in the decomposition of the direct sampling operations, including the sampling and down-sampling, and NSCT is completed on the corresponding filter sampling operation. Its structure is based on a conversion of non- sampling and a pyramid structure in the direction of non- sampling filter with decomposition, using α trous algorithm and generating a flexible multi-scale , multi-directional cut translation invariant image decomposition method. NSCT corresponding filter in the frequency domain with a better selection of rows and regularity, Contourlet transform compared with the design of the filter no longer have a lot of restrictions, which make it possible to have better selectivity filter with a frequency domain, and then get better subband decomposition, and then get better subband decomposition.

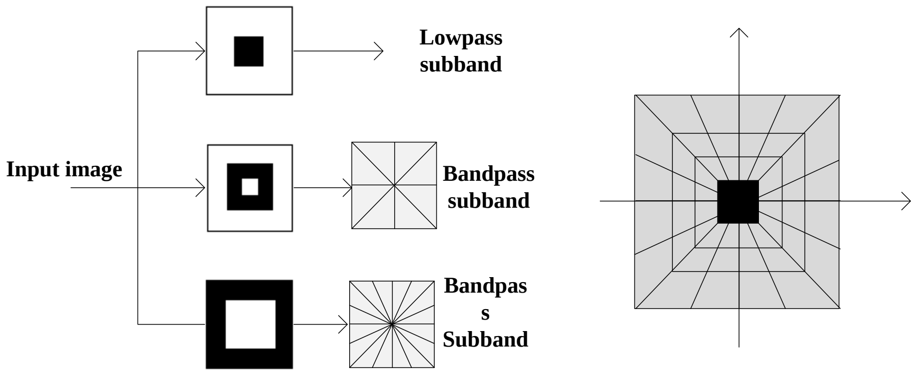

Figure 1. Nonsubsampled Counterlet Transform

Non-subsampled contourlet transform as shown in Figure 1. First, a non- sampling the input image to the pyramid is a low-pass sub-band decomposition of an image (low frequency component) and a band-pass sub-band image (high-frequency component), to achieve a multi-scale decomposition of the image; then use the direction of the non-sampling filter bank band-pass image is decomposed into a plurality of subband images subbands to achieve multi-directional image decomposition; Finally, each layer of the low-pass subband image repeats the above operation, to obtain a multilayer NSCT subbands of the input image. And after the image NSCT transform coefficients are sparse, thus CS can be used for decomposition and reconstruction.

3. Principle of CS

3.1 Compressed Sensing Process

Suppose x is one-dimensional discrete-time signal with the length of N , it can be expressed as a linear combination of a set of orthogonal basis

$$x = \Psi S \tag{1}$$

Where $\Psi = [\psi_1 \ |\psi_2| \cdots \psi_N \ ]$ is a $N \times N$matrix, ψ_i is column vector. S is a N × 1 column vector of the weighting coefficients of the sequence x . So S is equivalent represention of x. If S has K nonzero coefficients , when K≤N signal x is sparse or compressible x of K and S is sparse representation . In the course of the CS signal is not a direct measurement of sparse S itself, but the measured values obtained

$$y = \Phi x \tag{2}$$

Where $y \in R^M$, Φ is measured as M × N matrix.The (1) Substituted into the formula (2) type, obtained

$$y = \Phi \Psi S = \Theta S \tag{3}$$

Where$\Theta = \Phi \Psi$ is a M × N matrix. Compressed sensing measurement process shown in Figure 2. The purpose of the design is how the measurement matrix M observations obtained by sampling , and to ensure a small number of observations from the effective length of the reconstructed high N -dimensional signal x.

3.2. Reconstruction Algorithm

This paper uses the Orthogonal Matching Pursuit (OMP) as reconstruction algorithm [10]. Greedy iterative method is used to select Φ column ,then make the column selected in each iteration with the maximum degree of redundancy in the current vector related subtracted from the relevant part of the measurement vector and iteratively , know the number of iterations to achieve the sparsity M, this time to stop iteration. Specific steps are as follows:

First, the correlation coefficients are calculated as following:

$$u = \{u_j | u_j = |\langle r, \varphi_j \rangle|, j = 1,2,\cdots, N\} \tag{4}$$

And using the least squares method for signal approximation and the balance to update:

$$\hat{X} = \arg\min \|Y - \Phi_{\wedge} X\|_2 \quad i\epsilon R^{\wedge} \tag{5}$$

$$r_{new} = Y - \Phi_{\wedge} \hat{X} \tag{6}$$

The steps in detail are as following:

(1) Redundant initialization vector $r_0 = Y$, iterative point n = 1, the index set $\Lambda = \emptyset$, $J = \emptyset$.
(2) Calculate a correlation coefficient of u, and u corresponding to the maximum value of the index value stored in the J.
(3) Update support set Φ_Λ, where $\Lambda = \Lambda \cup J_0$.
(4) Applicate (1.2.2.1) to obtain X, while the formula (1.2.2.1) of the balance to be updated.

(5) If $\|r_{new} - r\| \geq \varepsilon_2$, make r $= r_{new}$, n = n + 1, go to step (2), otherwise stop iteration.
(6) Integration of medical image compression based on perception and NSCT.

4. Image Fusion in NSCT Domain

4.1 Fusion of Low Frequency Subband

The low frequency part of the image includes overall trend of image information, and the overall intensity of the image. For the low-frequency part, using mean rule for fusion is simple, easy to implement and fusion works well. The following is the rule of low-frequency part for the fusion method. $F_{low}(x,y)$ is the fused image pixel value at (x,y), $A_{i,j}(x,y)$ and $B_{i,j}(x,y)$ are the pixel values obtained by the i-level and j-direction NSCT decomposition of source image A and source image B at (x,y), respectively.

$$F_{low}(x,y) = mean(A_{i,j}(x,y) + B_{i,j}(x,y)) \tag{7}$$

4.2 Fusion of High Frequency Subband

High frequency part mainly includes the details, edge and the contour information of the image, etc. Therefore, the fusion of high frequency information relates to the overall quality of the image. Taking into account that the local features of an image unusually cannot be expressed by one pixel, it is represented and embodied by a plurality of pixels at a local area. Among each pixel within a local region of an image often has the strong correlation. So in terms of high-frequency coefficients we use the fusion method based on the maximum energy of neighborhood area, the image of local features have been further reflected. In this paper, we use a 3 × 3 matrix neighborhood sliding high-frequency coefficients. From the each neighborhood we get the maximum value F_{Ahigh}、 F_{Bhigh}instead of the pixel value at that point. Figure 3 is the decomposition coefficients in the 3 × 3 neighborhood. A_m frequency coefficients represents the pixel value of the M-th pixel in the neighborhood of the decomposed image A. F_{Ahigh}express the maximum energy result in the 3 × 3 neighborhood of image A, instead of the pixel value at the A_5table. F_{Bhigh} express the maximum energy result in the 3 × 3 neighborhood of image B, instead of the pixel value at the B_5 table.

A_1	A_2	A_3
A_4	A_5	A_6
A_7	A_8	A_9

B_1	B_2	B_3
B_4	B_5	B_6
B_7	B_8	B_9

Figure 3. Neighborhood Coefficient

$$F_{Ahigh} = \frac{A_5}{|A_5|} max(|A_1|, |A_2|, \ldots |A_i|, \ldots |A_9|)\ (1 \leq i \leq 9) \tag{8}$$

$$F_{Bhigh} = \frac{B_5}{|B_5|} max(|B_1|, |B_2|, \ldots |B_i|, \ldots |B_9|)\ (1 \leq i \leq 9) \tag{9}$$

$$F_{high} = \begin{cases} F_{Ahigh} & |F_{Ahigh}| > |F_{Bhigh}| \\ F_{Bhigh} & |F_{Bhigh}| > |F_{Ahigh}| \end{cases} \tag{10}$$

Figure 4 is a detailed process of image fusion method proposed in this paper , first with NSCT transform the image of the high-frequency information to be transformed CS observations, and then each of the high-frequency information and observations obtained in the low-frequency information fusion, Then the high-frequency observations were reconstructed after fusion , finally fused image is obtained NSCT inverse transformation.

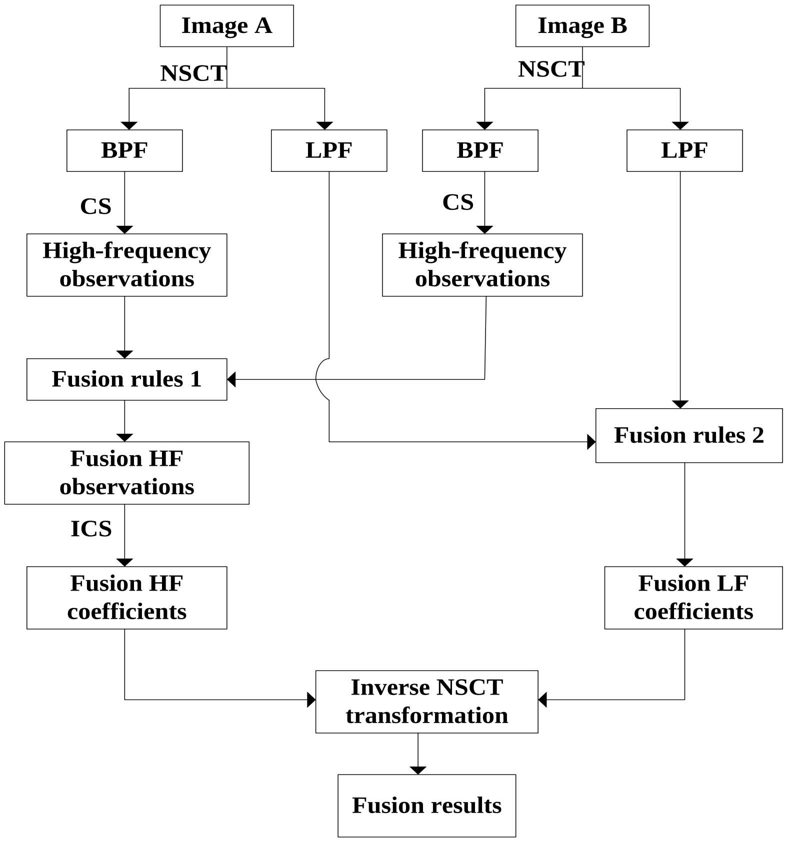

Figure 4. Image Fusion Flowchart based on CS and NSCT Transform

The following is specific implementation of the proposed imae fusion algorithm.

Input: medical image A and iamge B.

Step 1: Apply NSCT to image A and B respectively to get transform coefficients in low frequency subband and high frequency subband.

Step 2: Use mean rule to fuse the coefficients in low frequency subband of image A and B.

Step 3: Apply CS to the coefficients of high frequency subband for image A and B, then use neighbourhood-Max rule to fuse them and get the observation values. Apply OMP algorithm to perform CS reconstruction forget the coefficients in high frequency subband.

Step 4: Use inverse NSCT (INSCT) to the fused coefficients both in low frequency subband and high frequency subband to get the final image.

Output: fused medical image.

5. Experiments and Results Analysis

In order to verify the algorithm results, select medical CT images and MR images (size of 256×256) for fusion experiments. The two images from two sensors have different characteristics. The CT image brightness is related to tissue density, brightness of bone is higher in the CT image, and some soft tissues in CT images cannot be reflected. The number of hydrogen atoms of tissue is related the brightness in MR image. Soft tissue has high brightness and the skeleton information is not displayed in MR image. So fusion of complementary information of two images makes the information more clear and helps the doctor obtain medical diagnosis more accurate.

Experiments of medical image fusion are run based on MATLAB7.0. For the experimental results we used the following indicators to determine the assessment, including peak signal to noise ratio(PSNR), cross–entropy (CERF), mutual information(MI), edge information(QABF), entropy(H), spatial frequency information(SF), average gradient(AVE). PSNR indicates how many the useful information content of images. CERF reflects the difference between the two figures. H is a physical measure of the richness information contained in an image. AVE reflects extent of image detail and texture changes. Spatial frequency is used to evaluate the overall activity level of the image space. MI measures the information amount from source image. Above all, the values of PSNR, MI, QABF, H, SF, AVE are bigger, and the CERF is smaller, the fusion result is better.

Because full consideration to each image pixel in the region is corellated, local features of the image not by a pixel can be characterized and embodied, so this paper uses a regional energy whichever is greater in the high-frequency coefficients of the fusion process. We tried the fusion in high frequency subband by two ways. The first method, after NSCT transform, high frequency coefficients are processed CS transform, then taking maximum neighborhood energy integration of the CS observations coefficient, finally inverse CS transform and inverse NSCT transform. The method of the high-frequency selected region energy observed coefficients considering the relationship between the pixels after CS transform. We called this method CS-NE-MAX1. Method 2, first take maximum neighborhood energy of NSCT transform coefficients in high-frequency subband, then processed CS transform to obtain the high frequency observed value, thus fuse the high frequency observed value. Finally processed inverse CS transform and inverse NSCT transform for the high-frequency observations coefficients The method considers the relationship NSCT transform coefficients, called CS-NE-MAX2. Table 1 below shows the fusion results by different methods for comparison, including our proposed CS-NE-MAX1 and CS-NE-MAX2, method of compressed sensing to using max value (CS-MAX) and mean (CS- MEAN) in high frequency subband and the wavelet transform method (WT-MAX).

Table 1. Fusion Results of Different Methods

Methods	PSNR	CERF	MI	QABF	H	SF	AVE
WT-MAX	31.175	2.879	14.189	0.027	5.168	6.536	0.022
CS-MAX	30.923	2.946	14.013	0.244	5.158	4.322	0.012
CS-MEAN	30.921	2.957	13.971	0.243	5.151	4.283	0.012
CS-NE-MAX1	33.753	2.222	14.757	0.677	5.954	8.078	0.021
CS-NE-MAX1	33.592	2.284	14.579	0.613	5.997	6.139	0.017

It can be seen from Table 1, in the objective evaluation of the indicators, the method of this paper has better evaluation index except AVE. For the fusion method based on compressed sensing, our proposed methods including CS-NE-MAX1and CS-NE-MAX2 are significantly superior to the literature [8, 9, 11] proposed to get the maximum or mean of the coefficients. On the other hand, out two methods get equal image fusion results. But taking into account of CS-NE-MAX1 processed CS transform and then in the neighborhood take maximum energy. Thus the amount of data to be processed is small, and processing time is short. Therefore in the course of application we choose CS-NE-MAX1 method.

Figure 5 shows the fusion images by different methods. Among them, the Figure 5 (a) is a CT image, (b) is a MR image, and (c), (d), (E), (f), (g) respectively are the fusion results of WT-MAX, CS-MAX, CS-MEAN and CS-NE-MAX1 and CS-NE-MAX2 proposed in this paper. It can be seen that the fused images obtained by our methods keep the information in the edge region and texture information much better than other methods.

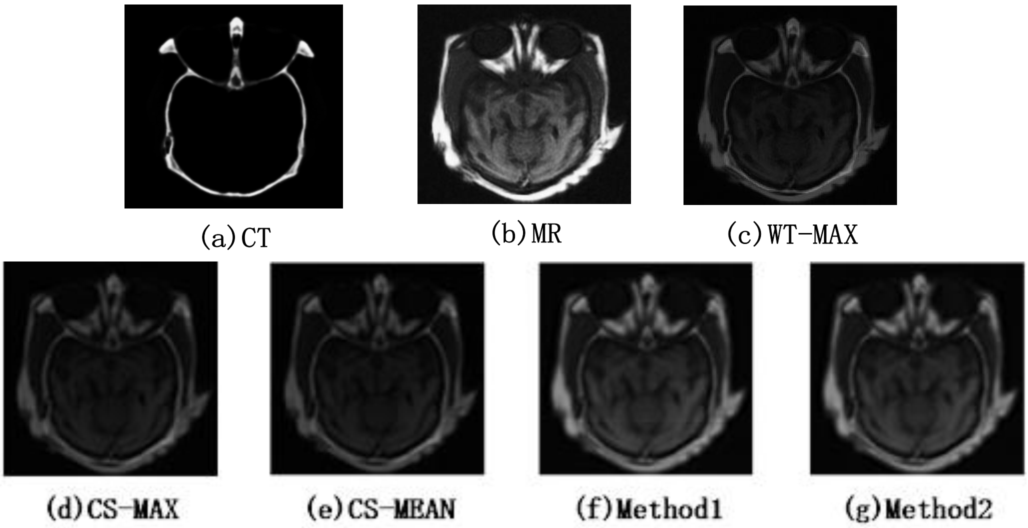

Figure 5. Fusion Results Comparison by Different Methods

Based on the experimental results above, this paper also studied the selection of region size has effect on the image fusion results. Table 2 gave the results of CS-NE-MAX1 fusion with the size of region is 3 × 3, 5 × 5 and 7 × 7.

Table 2. Fusion Results by Different Size of Neighborhood Area

Area size	PSNR	CERF	MI	QABF	H	SF	AVE
3 × 3	33.623	2.261	14.531	0.409	6.015	6.109	0.017
5 × 5	33.753	2.222	14.757	0.677	5.954	8.078	0.021
7 × 7	33.492	2.254	14.600	0.405	6.040	6.168	0.017

Integration results in Table 2 indicate, when selecting the maximum energy in the area, select slide matrix size of 5 × 5 can get better fusion result. Because the selection of matrix size of 5 × 5 has more correlation than that of3 × 3. When the matrix size reaches 7 × 7, due to the pixel distance gets larger and the correlation is reduced, so in this case in the area of 7 × 7 takes the maximum value of the region, resulting in no good result of fusion comparing to that of 5 × 5. Therefore, in practice, we select the area size of 5 × 5 for energy selection.

Below we analyzed the influence on fusion results by different decomposition levels of NSCT. Table 3 shows the result of the experiment, the fusion method is CS-NE-MAX1 and the size of the region selects 5 × 5. ({i, j} represents i decomposition for layer j directions of NSCT for the image). From Table 3 we can conclude that fusion results of the images with 3-layer decomposition are better than that of 4-layer decomposition. And with the same layer decomposition, results of decomposition of 8 directions and 4 directions are almost the same. Therefore, in practice we use {3, 4} for NSCT decomposition, and then follow the fusion process.

Table 3. Fusion Results of Different Decomposition Levels for NSCT

Decomposition level	PSNR	CERF	MI	QABF	H	SF	AVE
{4,8}	34.466	2.242	14.693	0.440	6.070	6.426	0.017
{4,4}	33.817	2.278	14.685	0.438	6.071	6.406	0.018
{3,8}	32.752	2.223	14.746	0.678	5.950	8.071	0.023
{3,4}	32.753	2.222	14.757	0.677	5.954	8.078	0.021

6. Conclusion

CS theory has a low sampling rate, low energy consumption characteristics and other characteristics. The amount of data obtained by sampling based on CS theory is far lower than the amount of data obtained by the Nyquist sampling, so it saves storage space and reduce the computational overhead. This paper presents a medical image fusion method based on CS theory in NSCT domain, and experiments show that the method in terms of subjective visual or objectively indicators have certain advantages.

Also, in this paper we analyzed the selcction of energy neighborhood size, NSCT decomposition level and number of direction. When the image is performed by 3-layer and 4 directions NSCT transform and selects the maximum energy by 5 × 5 neighborhood , fusion results is better than other decomposition style.

This medical image fusion algorithm proposed in this paper reflects the CS has potential advantages in image fusion application field. But we did not research on the selected measurement matrix in this paper, which is the next research direction in future.

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