A Novel Fusion Technique for CT and MRI Medical Image Based on NSST

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Abstract: In the field of CT and MRI medical image fusion, For the calculation complexity problem of image fusion based on non-subsampled contourlet transform(NSCT), a novel CT and MRI medical image fusion algorithm is proposed based on non-subsampled shearlet transform (NSST) and compressive sensing(CS) theory. Firstly, NSST is employed to decompose source images respectively, getting one low-pass sub-image and some band-pass directional sub-band images, which have the same size as source images. Secondly, using the improved weighted fusion rule to fuse the low-pass sub-band coefficients, to improve the problem that the contour of the fused image is fuzzy based on the traditional rule, meanwhile, for band-pass directional sub-band coefficients which are featured with high calculation complexity, the fusion rule based on CS is employed, namely, to use compressive sampling technology to sample band-pass directional sub-band coefficients, making a few of observations participate in the calculation of the fusion, to improve the execution speed of codes. Finally, utilizing the inverse NSST to obtain the final fusion image. Experimental results show that the proposed algorithm not only enriches details of the fusion image, but also reduces the calculation complexity ,in addition, the proposed improves the problem that the traditional multi-scale decomposition methods for image fusion bring out “Gibbs” effect.

Key Words: CT, MRI, Medical Image Fusion, NSST, CS

1 INTRODUCTION

With the rapid development of medical imaging technology, the medical imaging has become an important part of the clinical diagnosis. Clinical diagnosis requires that medical images have high resolution and can make the bone tissue, soft tissue show comprehensively, clearly. Obviously, the single modal medical image is unable to meet the requirement of medical diagnostics in [1].In details, CT (computed tomography imaging) and MRI (magnetic resonance imaging) is two common imaging in the modern clinical. CT uses the value of gray level to reflect the degree that organs and tissues absorb X rays, it shows the bone tissue clearly, but the soft tissue such as the lesion is vague, and CT can provide the reference for the location of the lesion. While, MRI can show the low density soft tissue such as blood vessels and the image of the lesion clearly. Therefore, the fusion of CT and MRI medical image from different models, will provide more intuitive, more accurate and more reliable basis for the modern clinical medicine diagnosis in [2]and [3]. At present, the method of medical image fusion based on multi-scale decomposition is the hotspot. For example, the wavelet transform with good time-frequency localization properties, is widely used for the field of medical image fusion, however, the wavelet transform can only expressed “point” singularities effectively, for the image having the linear singular feature, it is not the optimal approximation form. So,2002, Do etal. proposed the contourlet transform theory in [4], which not only retains the feature of time-frequency analysis, but also has the good directionality and anisotropy. However, the process that the contourlet transform decomposing image exists the down-sampling, so it doesn’t have the translation invariance. In order to solve this problem, 2006,Arthur L.d a Cunha proposed a non-sampling the contours transform (NSCT) in [5], NSCT is the contourlet transform with the translation invariance, which have been used for image fusion widely.For example, Nasrin Amini etal. applied NSCT to the image fusion successfully in reference [6] and [7]. While, due to the computational complexity of NSCT is high, it needs a lot of time when handling actual medical images, limiting its application. So, GUO proposed a new sparse representation for the high dimensional signal, it is the shearlet transform in [8], then, Easley put forward an improved non-subsampled shearlet transform(NSST) with the translation invariance in [9]. NSST and NSCT have the similar decomposition process, but the direction number of the shearlet in NSST is not restricted, and NSST allows different numbers of directiones each scale decomposition, besides, NSST can achieve the optimal sparse representation for images, thus reducing the probability of “Gibbs” effect in the the image processing. In addition, the mathematical structure is more simple than NSCT, means that NSST can reduce the computational complexity. Some scholars begin to prove that NSST has the superiority in

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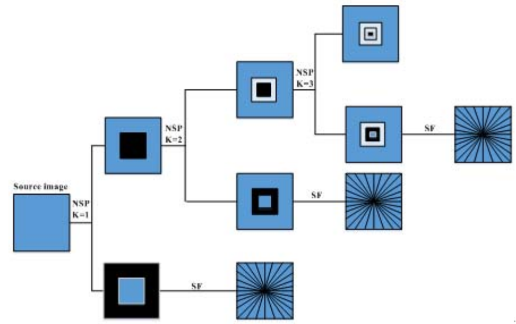
the field of the image fusion in[10].

Another core of multi-scale fusion method is to design the rule in transform domain. Employing NSST to decompose source medical images, obtaining a low-frequency sub-band and several band-pass directional sub-bands. For the fusion of the low-pass sub-band, the traditional rule is mainly the weighted average fusion rule, which reduces the contrast of the image, resulting to that important parts are not clear. To best integrate low frequency characteristics from source images, this paper adopts an adaptive weighted fusion strategy to fuse low-frequency sub-band coefficients, to improve the precision of the fusion result. For high-frequency directional sub-band coefficients having high complexity, using compressive sensing technology in [11] to achieve the fusion result. Firstly, taking compressive sampling to sample high-frequency directional sub-band coefficients, to get a few of observations, then, using a few of observations to participate in the calculation of image fusion, finally, reconstructing the fused observations by the optimal solution to obtain the fused high frequency coefficients, thereby, the amount of computation is reduced in the process of image fusion.

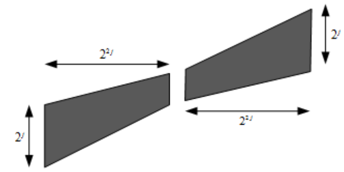
According to above analysis, this paper proposes an improved CT and MRI medical image fusion algorithm based on NSST. For low-frequency coefficients, an adaptive weighted method is utilized to fuse them. Meanwhile, the fusion rule based on CS is employed to fuse high frequency coefficients. Experimental results show that our method not only improves the quality of the fusion result, but also perfects the efficiency for the medical image fusion.

2 NSST

The discrete process of NSST is divided into the multi-scale decomposition and the direction decomposition, the process of NSST decomposition is shown as Fig.1(a), the corresponding frequency support base is shown as Fig.1(b), the detail principle of NSST can be found in [9]. Multi-scale decomposition is achieved by non-subsampled sampling pyramid(NSP), which is similar to NSCT. If the image is decomposed through k levels of NSP decomposition, we will get $k + 1$ sub-images, including 1 low-pass sub-image and k band-pass sub-images, the size is the same as the source image and the scale is different. However, NSST adopts the shearlet filter(SF) to achieve the direction decomposition, giving up the direction filter of NSCT. The standard shear filter in NSST is mapped from the pseudo polarization grid system to the cartesian coordinate system, using Fourier transform can prove that the operation can be performed directly by the two-dimensional convolution, avoiding sub-sampling operations. So, NSST has the translation invariance. Due to the direction filter of NSST can be represented by a window function ,which is in the form of a matrix, the aspect ratio in interval changes over scales, and NSST can decide how much directions, according to the need of the time complexity and the fusion quality, thus solving the problem that non-subsample directional filter bands of NSCT exist restricted directions. Therefore, NSST not only retains the local flexibility and effectiveness of NSCT, but also solves the problem that directions are limited when NSCT decompose the image.



(a) the process of 3 levels NSST decomposition



(b) the frequency support of NSST

Figure 1: the process of NSST decomposition and the frequency support

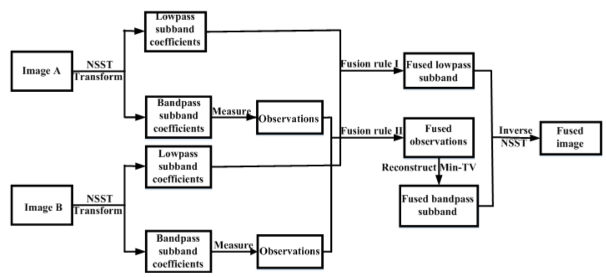


Figure 2: the improve fusion scheme for medical images based on NSST

3 The Improved Medical Image Fusion of CT and MRI Based on NSST

Aiming at CT and MRI medical image fusion, this paper puts forward an improved fusion method for medical images based on NSST. Firstly, utilizing NSST to decompose the registered source image respectively, then, obtaining the corresponding low-pass sub-band and several band-pass directional sub-bands. the adaptive weighted fusion rule is used to fuse low frequency sub-band coefficients, and the fusion rule based on CS is employed to fuse high frequency sub-band coefficients with high complexity. The proposed fusion scheme is shown as Fig.2.

Main steps as follows:

- Decomposing Image A and B by NSST into low-pass sub-band coefficients$\{L^A,L^B\}$and band-pass directional sub-band coefficients$\{H^A_{l,k},H^B_{l,k}\}$,where, L represents the low-pass sub-band coefficient, $H_{l,k}$ represents band-pass directional sub-band coefficient at the scale l and the direction k;

- Fusing low-pass sub-band coefficients based on the fusion rule described in Section 3.1, to get the fused low-pass coefficient F^{low}

- Using Toplitz matrix to measure $H_{l,k}^A$ and $H_{l,k}^B$, to get observations $X_{l,k}^A$ and $X_{l,k}^B$, here, the number of $X_{l,k}$ is more less than $H_{l,k}$.
- Fusing $X_{l,k}^A$ and $X_{l,k}^B$ according to the rule in Section 3.2.2, to obtain fused observations $Z_{l,k}^{F,high}$ in CS domain;
- Employing min-TV algorithm according to formula(7),to reconstruct the fused and sparse band-pass sub-band $F_{l,k}^{high}$ from $Z_{i,k}^{F,high}$.
-)Reconstructing F^{low} and $F_{l,k}^{high}$ by NSST inverse transform, to gain the final fused image F.

3.1 The Fusion of Low-pass Sub-band

Low-frequency coefficients obtained by NSST decomposition, mainly reflecting general features and approximate information of the original image. Commonly, the weighted average rule is employed to fuse low frequency sub-band coefficients, ignoring the overall effect of low frequency coefficients on images. In order to synthesize low frequency characteristics of source images better, this paper adopts an adaptive weighted fusion rule for low frequency coefficients as(1),

$$F^{low}(i,j) = [(L^A(i,j)+\lambda L^B(i,j))-|L^A(i,j)-\lambda L^B(i,j)|]\alpha \tag{1}$$

Where, $F^{low}(i,j)$ is the fused low frequency sub-band, α and λ are parameters. Within, the first half part is $(L^A(i,j) + \lambda L^B(i,j))\alpha$,which is the weighted add of low frequency coefficients from two source images, impacting the energy of the fused image, and deciding the brightness of the fused image. And, the second half part is $|(L^A(i,j) - \lambda L^B(i,j)|\alpha$,which stands for the absolute value of the weighted difference of low-frequency coefficients, containing the edge information of the source image, called as the fuzzy factor. In details, λ regulates the dominant proportion of two low-pass sub-images, making two low-pass sub-images having different brightness reach balance. With the increasing of α, the brightness of the fused image is bigger and the edge is enhanced. Accurately, the value of α and λ is decided according to the characteristics of two low-pass sub-images, in this paper, we determine the value of α and λ according to these two parameters, such as the average gradient and spatial frequency, shown as formula(2) and (3).

$$\begin{cases} \alpha = AG(L^A)/(AG(L^A + AG(L^B)), AG(L^A) \geq AG(L^B) \\ \alpha = AG(L^B)/(AG(L^A + AG(L^B)), AG(L^A) < AG(L^B) \end{cases} \tag{2}$$

$$\begin{cases} \lambda = SF(L^B)/SF(L^A) + 1, SF(L^A) \geq SF(L^B) \\ \lambda = SF(L^A)/SF(L^B) + 1, SF(L^A) < SF(L^B) \end{cases} \tag{3}$$

Where, $AG(L^A)$ and $AG(L^B)$ represent the corresponding average gradient of the low frequency sub-image L^A and L^B respectively, also, $SF(L^A)$ and $SF(L^B)$ represent the corresponding spatial frequency of L^A and L^B respectively.

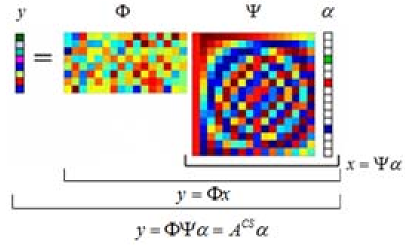


Figure 3: Process of CS measurement

3.2 The Fusion of Band-pass Sub-band

The high frequency coefficients obtained by NSST decomposition mainly represent the detail and the texture of the source image, and high frequency coefficients are sparse, meeting the requirement of CS theory. Therefore, applying CS to the fusion of high frequency sub-band coefficients, can reduce computation time of the fusion.

3.2.1 CS Theory

Considering a real-valued, finite-length and one-dimensional discrete time signal$x \in R^N$,according to the signal theory, It can be represented as(4),

$$x = \Psi\alpha \tag{4}$$

Where,Ψ represents an $N\times N$ basis, and α is an $N\times 1$ vector, containing only K non-zero coefficients. If $K \ll N$, w e can say that x is compressive, Ψ is the sparse base, and α is the sparse signal of x in Ψ domain. Then, we can design an $M\times N$ measurement matrix $\Phi(M \ll N)$,multiplying Φ by x to achieve the compressive sampling for the signal x as formula(5), where,$y \in R^M$ represents the measurement value, and $A^{CS} = \Phi\Psi$, the process of CS measurement is shown as Fig.3.

$$y = \Phi x = \Phi\Psi\alpha = A^{CS}\alpha \tag{5}$$

Goldstain.T proved that Toplitz matrix can be a universal compressive measurement matrix , which is not only irrelevant with almost sparse bases, but also meets RIP feature matrix in [12],and Toplitz matrix is easy physical implementation. So the toplitz matrix is employed as the measurement matrix in this paper, utilizing the compressive measurement matrix, we can get less of observations than the number of the source signal, reducing the storage of data.

When data finish the transmission ,we want to decode the source data, How to do can get the source signal ? the answer is to solve the formula(5),the process of solving(5) is called as the compressive reconstruction. Because M is far smaller than N,(5) is an ill-conditioned equation. Numerous studies show that, for the compressive signal, if Φ and Ψ meet RIP feature, we can first recover the sparse signal α, then, multiplying α by Ψ to get the original signal

x. Candes shows that we can recover the sparse signal α exactly by solving the problem as formula(6),

$$min\|\alpha\|_1 \quad s.t. \quad y = A^{CS}\alpha \tag{6}$$

(6) is a convex optimization problem known as basis pursuit(BP),the improved version is called as orthogonal matching pursuit(OMP) algorithm, which is easy to implement and has fast computation speed.OMP is especially suitable for the recovery of one-dimensional signals. Then, Candes proposed the min-TV model for 2-D images based on its gradient is sparse in [11]. Min-TV has better robustness than OMP, which can perfectly accomplish compressive reconstruction for images. We employ min-TV algorithm to achieve the reconstruction of the sparsity α as (7),

$$minTV(\alpha) \quad s.t. \quad y = \Phi\alpha \tag{7}$$

The objective function $TV(\alpha)$ is the sum of the discrete gradient of the image, defined as(8)

$$TV(\alpha) = \sum_{i,j} \sqrt{(\alpha_{i+1,j} - \alpha_{i,j})^2 + (\alpha_{i,j+1} - \alpha_{i,j})^2} \tag{8}$$

3.2.2 The Fusion Rule of Band-pass Sub-band observations

Aiming at the fusion method based on multi-scale analysis, if the coefficient in frequency domain is bigger, that means the coefficient contains more information. Because the process of CS measurement is a linear process, the corresponding observation value of the high frequency coefficient also has a linear relationship with the high frequency coefficient.It is to say, if the observation value of the high frequency coefficient is greater, means that observations contain the information is larger, conversely, the information is less. So, we can first fuse observations of the high frequency sub-band coefficients, then, using optimization reconstruction algorithm (Min-TV) to reconstruct fused high frequency sub-band observations.

Firstly calculating the weights of high frequency sub-band observations from the band-pass sub-image $H_{l,k}^A$ and $H_{l,k}^B$ in each direction as(9), they are respectively $\omega_A^{(m)}$ and $\omega_B^{(m)}$.

$$\omega_A^{(m)} = \frac{|X_{l,k}^{A(m)}|}{|X_{l,k}^{A(m)}| + |X_{l,k}^{B(m)}|} \tag{9}$$

Where, $\omega_B^{(m)} = 1 - \omega_A^{(m)}$,*m=1,2,......,n*. m stands for each direction of NSST decomposition, n is the number of the orientation of NSST decomposition, then, the observation of the high frequency sub-image $H_{l,k}^A$ and $H_{l,k}^B$ in each direction is fused based on the rule as formula(10),

$$Z_{l,k}^{F,high(m)} = \omega_A^{(m)} X_{l,k}^{A(m)} + \omega_B^{(m)} X_{l,k}^{B(m)} \tag{10}$$

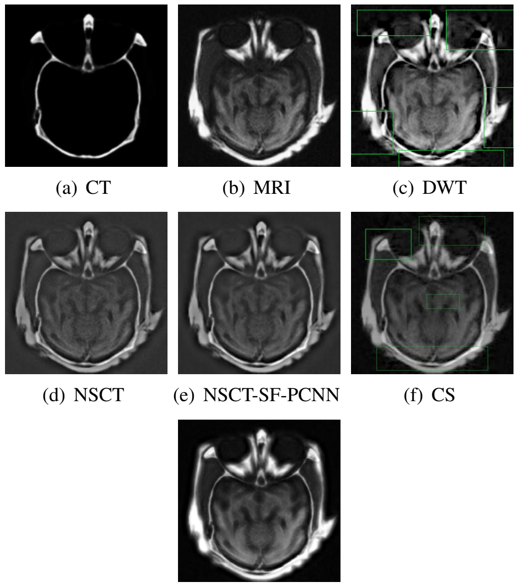
Where ,$X_{l,k}^{A(m)}$ and $X_{l,k}^{B(m)}$ represent respectively the observation of the band-pass sub-image $H_{l,k}^A$ and $H_{l,k}^B$ in different direction. $Z_{l,k}^{F,high(m)}$ represents the fused high frequency observations. Finally, employing min-TV algorithm to get the fused bandCpass sub-band coefficients.

4 Experiment Results and Analysis

The environment of experiment is the system of Win7 64-bit , CPU is 3.20GHz, Memory is 4GB, and the software is MatlabR2010. We prepare two groups of CT and MRI medical images to test. The first group is CT and MRI medical image of the brain of human beings, shown as Fig.4(a) and Fig.4(b).The second set is CT and MRI medical image of the patient with cerebral infarction, shown as Fig.5(a) and Fig.5(b). The size is all 256*256.

In order to verify the effectiveness of the proposed algorithm, we compare the proposed method with other four methods. In details,1).The image fusion method based on discrete wavelet transform, the same fusion rule as this paper is used to achieve the fusion of low frequency coefficients, the maximum of absolute value is used to obtain fused high frequency coefficients, and Db4 wavelet is used as the wavelet basis, called as DWT and marked as M1.2).The image fusion method based on NSCT mentioned in [13], the fusion rule of low-frequency and high-frequency coefficient is the same as method I above, called as NSCT and marked as M2.3).The fusion image method based on NSCT-SF-PCNN in [14], the fusion rule of low-frequency is the same as this paper, the fusion of high-frequency coefficients is based on SF-PCNN, called as NSCT-SF-PCNN and marked as M3.4).The fusion method base on CS proposed by X.Li in [15], called as CS and marked as M4. In this paper, the first step is to decompose two source images based on NSST, the second step is to fuse low frequency coefficients based on the adaptive weighted fusion rule to get the fused low frequency sub-band, at the same time, high frequency coefficients are fused based on CS, we call the proposed method as Ours. To compare experiment results effectively, we set the decomposition level of DWT,NSCT,NSST to 3 levels, and set the level of the directional sub-band of NSCT and NSST to [2,3,3].

In usual, we can evaluate the quality of fusion image from the aspect of subjective and objective. The subjective evaluation is usually done according to the visual of human beings, including the evaluation of the brightness, texture and clarity of the image, but the evaluation is susceptible, due to different people have different visual characteristics and mental state. However, the objective evaluation is more focused on quantitative analysis, which is more credible than the subject evaluation. Therefore, this paper first evaluates the fused image from the aspect of subjective, then, selects the object criteria to evaluate the fused image, including SSIM, Clarity, Information Entropy(IE) and (Q,Qw,Qe) which combining subjectivity with objectivity. Among them, SSIM is used to measure the similarity between two images, it is bigger that means the fused image containing more information from source images, but the maximum value is 1.Then,Clarity can reflect the expression ability for the contrast of tiny details, the value is greater means the image is more clear. Also, IE can reflect the amount of image information, the value is greater, that means the fused image having more rich information and better quality. Finally,(Q,Qw,Qe) can fully consider the human visual, and measure how much significant information



(a) CT (b) MRI (c) DWT (d) NSCT (e) NSCT-SF-PCNN (f) CS (g) Ours

Figure 4: source images and fusion results of first group

will be reserved from original images, especially can measure the distortion information of the source image .Also, the value is closer to 1, the quality of the fused image is better.

4.1 The First Fusion Experiment

Fig.4(a) and Fig.4(b) are CT and MRI medical images of the normal brain respectively, which have well been registered. Fusion results based on different methods are shown as Fig.4(c)-Fig.4(g), Fig.4(c) is the fusion image based on DWT, Fig.4(d) is the fusion result based on NSCT; Fig. 4(e) is the result based on NSCT-SF-PCNN, Fig.4(f) is the fusion image based on CS, Fig.4(g) is the fusion image based on our method.

From Fig.4, all methods can keep important information and the feature information from two source images, the result reserves not only the skeletal morphology of CT image, but also highlights blood vessels and other soft tissue information in MRI. But it is not difficult to find that the fusion result based on DWT has the obvious pseudo outline, called as “Gibbs” effect, shown as the rectangular box in Fig.4(c) , the reason is that the direction number of traditional wavelet is limited, it is only 3,and it can not realize the optimal sparse representation for the image. In addition, the result based on DWT has poor ability to extract details information of MRI image such as soft tissue, and the fusion image is too bright. The fusion image based on NSCT has low light and contrast, it can keep the skeleton and soft tissue information, but the expression is not clear, indicating that NSCT has the disadvantage of limited direction. The result based on NSCT-SF-PCNN can effectively improve the fusion result based on traditional NSCT by employing PCNN neural network, in details, taking SF to inspire PCNN neural network , to fuse high frequency coefficients in NSCT domain, the fused result is shown as Fig.4(e), we can find that the quality of the fusion image is better than NSCT. However, employing PCNN neural network in NSCT domain will greatly increase the computational complexity. The fused image based on CS is shown as Fig.4(f), the quality and efficiency are relatively good, however, X.Li uses Fourier as the sparse basis, we know Fourier is not the optimal sparse representation for the two-dimensional image, so the fusion result also exists ”Gibbs” phenomenon ,which can be found according to the green rectangle in Fig 4(f). All above, the proposed method can get the fused image with the highest clarity, the optimal contrast and the best visual effect, besides, compared with NSCT and NSCT-SF-PCNN, it also reduces the time of the fusion process.

Table 1: Comparison of objective criteria for the first group

Criteria	SSIM	Clarity	IE	Q	Qw	Qe	Time/
M1	0.6701	6.9381	6.9440	0.6457	0.6082	0.6193	8.2
M2	0.6722	6.9617	6.8973	0.6653	0.6291	0.6328	145.1
M3	0.6793	7.2983	7.0018	0.6695	0.6487	0.6360	160.9
M4	0.6851	7.7071	7.1092	0.6721	0.6605	0.6443	3.4
Ours	0.7240	8.8113	7.3325	0.6917	0.6842	0.6586	41.0

Objective criteria based on above five methods are listed in Table1, it can be seen that our method is superior than others, because all criteria based ours show obvious superiority. In Table1, Objective criteria of DWT is worst except for the criterion IE, and the time based DWT is 8.2s. It is not difficult to find that CS method has the shortest time, so it can widely be applied in the real-time fusion system, and all of object criteria based on CS are good, Other two methods based on NSCT and NSCT-SF-PCNN spend a lot of time, and the method based on NSCT-SF-PCNN is the most time-consuming, but the object criteria is better than NSCT. From Table 1,we can find that our method spend 41.0s, which is about 1/4 times of the fusion time based on NSCT. In short, experimental results show that the proposed method is the best from comprehensive evaluation of various criteria.

4.2 The Second Fusion Experiment

To further verify the robustness of our method, we select another group of CT and MRI medical images of patients with cerebral infarction to experiment, shown as Fig.5(a) and Fig.5(b). The fusion images based on different methods can be seen in Fig.5(c)-5(g), Fig.5(c) is the fusion image based on DWT, Fig.5(d) is the experiment result based on NSCT, Fig.5(e) is the fused result based on NSCT-SF-PCNN, and Fig.5(f) is the fusion image based on C-S, Fig.5(g) is fusion result based on the proposed method in this paper. From the visual analysis, the blood vessels, hemorrhage information of MRI imaging and the neurocranium bone information of CT imaging based on above five methods can reserved entirely, but these results have difference. DWT still bring out the pseudo ”Gibbs” phenomena, marked as the rectangular box in Fig.5(c). The NSCT fusion method get dark and less contrast image, NSCT-SF-PCNN improve the fusion effect than NSCT , but it is still not perfect. The fusion image based on CS has similar effects as the first group, and the false contour phenomenon

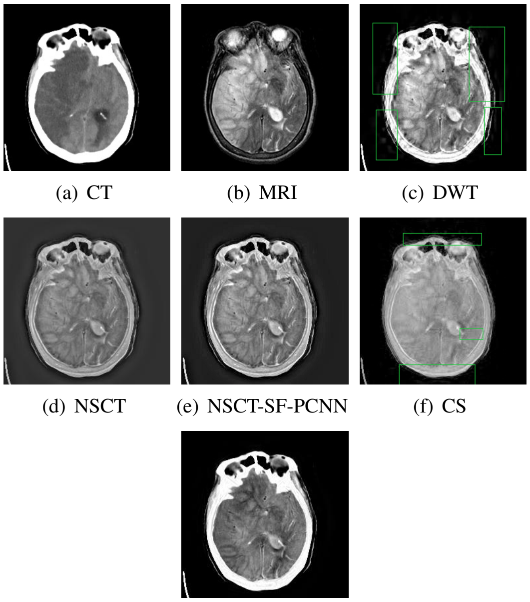

(a) CT (b) MRI (c) DWT
(d) NSCT (e) NSCT-SF-PCNN (f) CS
(g) Ours

Figure 5: source images and fusion results of second group

Table 2: Comparison of objective criteria for the second group

Criteria	SSIM	Clarity	IE	Q	Qw	Qe	Time/s
M1	0.6901	7.6551	8.7732	0.6209	0.6144	0.5973	9.5
M2	0.6868	6.9773	7.8326	0.6185	0.6192	0.5864	156.3
M3	0.7637	8.2185	9.0170	0.6393	0.6317	0.6221	180.3
M4	0.7062	7.9114	8.8433	0.6101	0.6084	0.5792	5.4
Ours	0.7813	8.2866	9.2121	0.6524	0.6373	0.6276	59.7

still exists, shown as Fig.5(f). From Fig.5(g), our method not only retains a large amount of details information, but also has the best lightness and contrast.

Table2 lists objective criteria of the second group based on above five methods. All criteria of the proposed method is superior than other four methods, further proving that our method shows an obvious advantage in the field of medical image fusion, For example, Q ,Qw,Qe are respectively 0.6524, 0.6373, 0.6276 ,which are better than others, and our other objective criteria are also the best. In a word, the second group of medical images further verifies the effectiveness and superiority of the proposed method.

5 Conclusion

In this paper, taking the advantage of NSST to achieve the fusion of CT and MRI medical image, meanwhile, combining the compressive sensing theory, an improved CT and MRI medical image fusion method is put forward, which not only effectively improves the ability of the fusion image preserving details , but also overcomes the problem that the high calculate complexity of NSCT. Firstly, employing NSST to decompose the source images, to get the low frequency and high frequency coefficients. Secondly, the adaptive weighted fusion strategy is employed to fuse low frequency coefficients, for high frequency sub-band coefficients with the high computational complexity, the fusion rule is adopted based on CS, effectively reducing the calculation time. Finally, experimental results show that CT and MRI medical image fusion based on ours can not only make the fusion image better express the edge, texture and structure characteristics, but also reduce the computational complexity. However, looking for the optimal approximation for images, from the perspective of approximation theory, is the key to improve the quality of the fused image, it is also the difficult work in the future.

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