

## MEDICAL IMAGE FUSION BASED ON NONSUBSAMPLED DIRECTION COMPLEX WAVELET TRANSFORM

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### Abstract

Combined with the advantage of more low-frequency sub-bands coefficients in nonsubsampled direction filter bank-dual-tree complex wavelet transform (NSDFB-DTCWT), a medical image fusion algorithm based on NSDFB-DTCWT is proposed to overcome the complexity fusion rules in image fusion algorithm based on the multi-scale multi-resolution transform. First, NSDFB-DTCWT is utilized for decomposition of the source images, and then the maximum of the absolute value of all frequency coefficients of decomposition is selected to construct fusion image. Finally, the fusion image is gained after

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inverse NSDFB-DTCWT. The algorithm can both make effective use of the contour information of source images and preserve the details of source images. What's more, its fusion strategy is very simple and has low computation cost. Experimental results demonstrate that the proposed method can not only obtain good visual effect, but also improve its objective evaluation.

*Keywords:* fusion, medical image fusion, NSDFB-DTCWT, complex wavelet transform, nonsubsampling direction filter bank formation.

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## 1. Introduction

The processing to obtain a panorama relatively clearer, easier to understand, and the identification image by using complementary and redundant information of multiple images of the same medical organ from different sensors is defined as medical image fusion. This paper focuses on the pixel-level medical image fusion technology. Pixel-level image fusion method can be divided into two categories: Spatial domain algorithms and transform domain algorithms [1]. Spatial domain algorithms include weighted mean fusion algorithm [2] and principal component analysis (PCA) fusion algorithm [3], etc. While the transform domain algorithms mainly include the image fusion algorithm based on wavelet or multi-scale geometric transform. For example, [1] gave fusion algorithm based on wavelet, [4] gave fusion algorithm based on contourlet transform (CT), and [5] gave fusion algorithm based on non-subsampling contourlet transform (NSCT).

Currently, image fusion algorithms based on multi-scale geometric transform are the hot topic. The fusion methods based on CT and NSCT [5, 6] is very important in this issues. Medical image fusion algorithms based on multi-scale geometric transform are also the main stream algorithms, such as the authors proposed a medical image fusion algorithm based on redundant discrete wavelet transform in [7], and [8] also gave a medical image fusion algorithm by using CT.

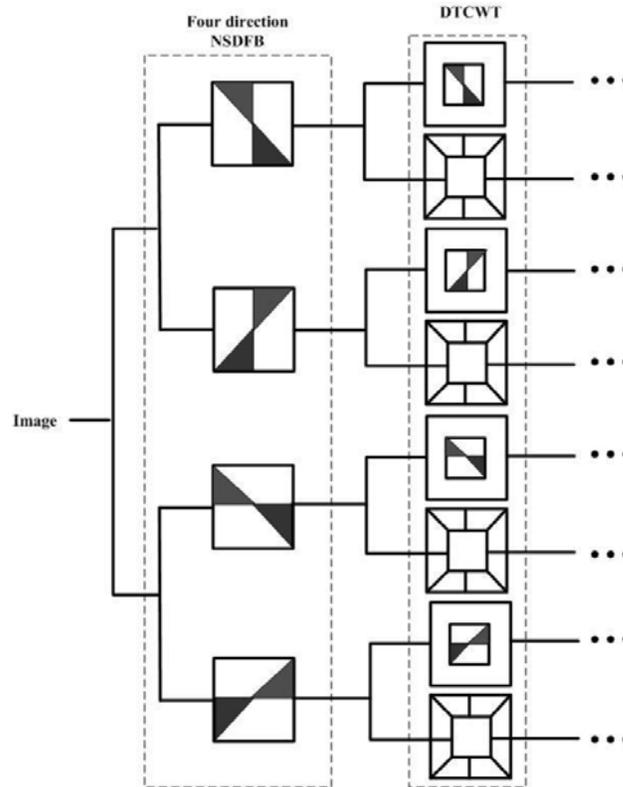
Although some good results had been achieved based on the above image fusion algorithms, but it can be seen that these algorithms all have only one low-frequency sub-bands. And, we know that the low frequency sub-bands contain almost all the contour information of image. So fusion algorithms based on these transform certainly affect the effect of the fusion. In order to achieve a better fusion results, most of the fusion rules are very complex. Therefore, we use NSDFB-DTCWT which is proposed in [9] to decompose the source image which should be fused, and this transform can effectively increase the low-frequency coefficients. It is beneficial to maintaining the contour and improving the effect of image fusion. This paper presents a medical image fusion algorithm based on NSDFB-DTCWT. The decomposition by NSDFB-DTCWT has greatly increased the low frequency coefficients, which reduces the contribution of high-frequency coefficients in image fusion. So, the fusion rule in high sub-bands coefficients does not require complex high-frequency sub-bands coefficients fusion rules. Therefore, in this paper, regardless of high frequency or low frequency sub-bands coefficients, we use maximum of the absolute value of coefficients to fuse the medical image. Experimental results show that our algorithm's visual effect has been significantly improved, the objective evaluation criterion has a certain improvements, and computation time also is decreased.

This paper is organized as follows. In Section 2, we review the construction of NSDFB-DTCWT and its property. In Section 3, we present a medical image fusion based on NSDFB-DTCWT. In Section 4, we show the numerical results. Finally, we present some discussions and conclusions in Section 5.

## 2. The Construction of NSDFB-DTCWT

Complementary fan filters are the basic module of NSDFB. Its up-sampling and linear transform lead to the characteristics of different direction frequency supporting [6]. Whatever the decomposition scales is larger or small, the redundancy of DTCWT is always 4. Some papers give proof that the form based on dual-tree filter can both ensure the perfect reconstruction and retain the good properties of complex wavelets in DTCWT. What's more, DTCWT is almost shift-invariant by designing special wavelet function [10]. Therefore, we can combine NSDFB and DTCWT to construct a new anti-aliasing multi-scale multi-resolution transform with properties of shift-invariance and direction selectivity.

In [9], NSDFB-DTCWT is construction by a cascade of NSDFB and DTCWT. That is, each direction sub-bands is obtained by applying direction filter to image firstly. And then two low frequency sub-bands and six high frequency sub-bands are obtained by applying dual-tree complex wavelet transform to each direction sub-bands. Then, we can get the pyramid by repeating above operation to low frequency sub-bands like DWT. The reconstruction algorithm of NSDFB-DTCWT is in reverse order. The schematic diagram of NSDFB-DTCWT is shown in Figure 1.



Two DTCWT low sub-bands is contained in every low sub-bands, and six high sub-bands is contained in every high sub-bands of NSDFB-DTCWT

Figure 1. Schematic diagrams of NSDFB-DTCWT.

[9] gives the proof that NSDFB-DTCWT can both overcome frequency aliasing of CT and have the property of shift-invariance. From Figure 1, we can know, in NSDFB-DTCWT, there are six high frequency sub-bands fewer than CT and NSCT, but it has sufficient directivity; and there are more low frequency sub-bands than CT and NSCT. In the other words, NSDFB-DTCWT increasing the number of low frequency sub-bands by reducing high frequency sub-bands every scale. So, we can get a better fusion effect from more details of source images by dealing the low frequency sub-bands.

### 3. Medical Image Fusion Based on NSDFB-DTCWT

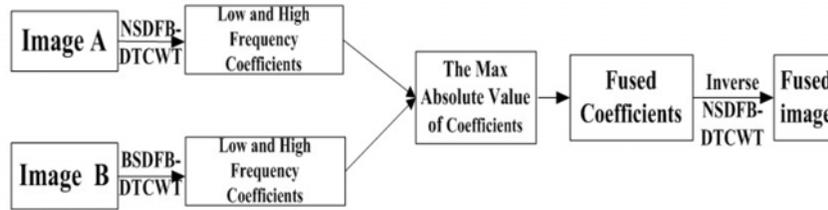
In image fusion based on transform domain, using the fusion rules of region energy to select coefficients has good fusion results, because the human visual system is not sensitive to a single pixel, but is sensitive to the image edge, direction and texture information and the fusion rules based on regional energy can satisfy the visual system well. But, the fusion rules of high sub-bands in [4, 5, 7, 8] are very complicated and affect the computation speed. The structure and the textures of medical image are simple and NSDFB-DTCWT has more low frequency sub-bands coefficients which can easily grab image structure, so we can use simple fusion rules in low-frequency and high-frequency sub-bands coefficients to achieve a satisfactory fusion effect and calculation speed.

The proposed image fusion algorithm is described as follows. Without losing of generality, we suppose that  $A$  and  $B$  are two medical images in different type to fuse,  $F$  is fused image. Obviously, it is easy to promote it into multiple image fusion.

First, we utilize NSDFB-DTCWT to decompose, image  $A$  and  $B$ , and the decomposition coefficients can be represented by  $C_A^{l,d}(k)$  and  $C_B^{l,d}(k)$ . Generally, the fusion coefficients are  $C_F^{l,d}(k)$ , where  $l$  and  $d$  denote the scale and direction of decomposition, respectively.  $k$  denotes the position of pixel. We use maximum of the absolute value of coefficients to construct the medical fusion images. The fusion rule is as Equation (1).

$$C_F^{l,d}(k) \begin{cases} C_A^{l,d}(k) & |C_A^{l,d}(k)| > |C_B^{l,d}(k)| \\ C_B^{l,d}(k) & |C_A^{l,d}(k)| \leq |C_B^{l,d}(k)| \end{cases} \quad (1)$$

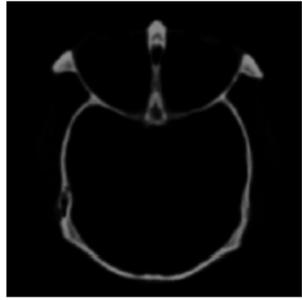
Finally, the fused coefficients  $C_F^{l,d}(k)$  are utilized to reconstruct the fused image  $F$  through inverse NSDFB-DTCWT. In conclusion, the framework of the proposed fusion algorithm is shown in Figure 2.



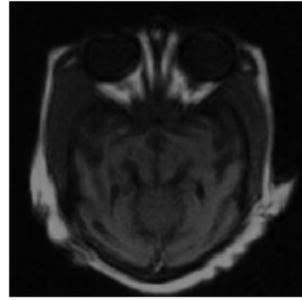
**Figure 2.** Schematic diagrams of NSDFB-DTCWT.

#### 4. The Numerical Results

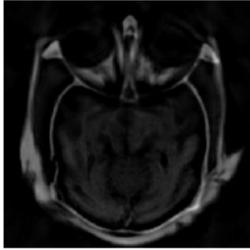
In order to evaluate the performance of the proposed method, we use common fusion medical test images to test it in terms of visual appearance and objective criteria. For comparison purpose, the fusion is also performed by using the fusion methods, which are proposed in [4, 5, 7, 8].  $Q^{AB/F}$  metric [4], mutual information (MI) [4], and spatial frequency (SF) [4] are employed as objective criteria.  $Q^{AB/F}$  measures the amount of edge information transferred from the source images to the fusion images, MI essentially computes how much information from source images is transferred to the fusion image, and SF can reflect the ability of retaining tiny details. The larger of the objective criteria values and the clear fused image we get, the better fusion performance a method has. In the experiment, the decomposition level of DWT, CT, and NSCT is 4, and there are 4, 8, 8, 16 direction sub-bands in each level direction filter, respectively. While the decomposition level of NSDFB-DTCWT is 2 as well, with 18, 18 directional sub-bands in each level direction filter, respectively. Figure 3(a) and 3(b) are classical medical fusion images. The size of these two images both are  $256 \times 256$ . The methods proposed in [4, 5, 7, 8] and our method are applied to fuse these image, respectively. The fused images and difference images (fused images minus the source image) are shown in Figure 3(c)-3(q).



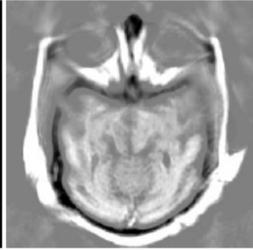
(a)



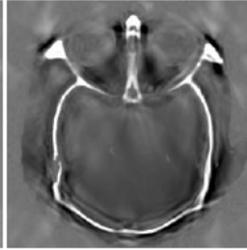
(b)



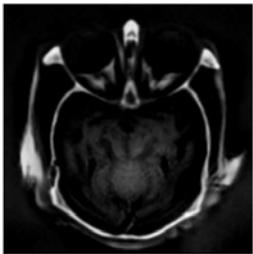
(c)



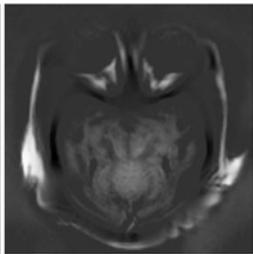
(d)



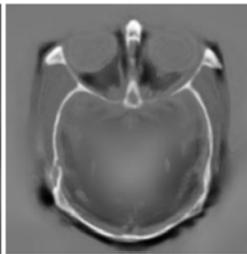
(e)



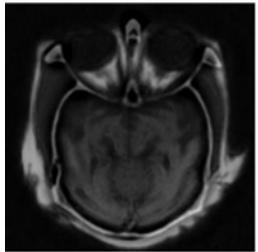
(f)



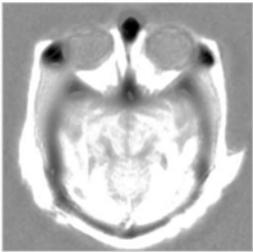
(g)



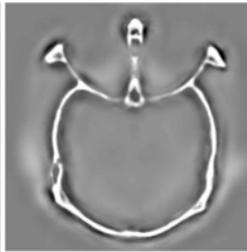
(h)



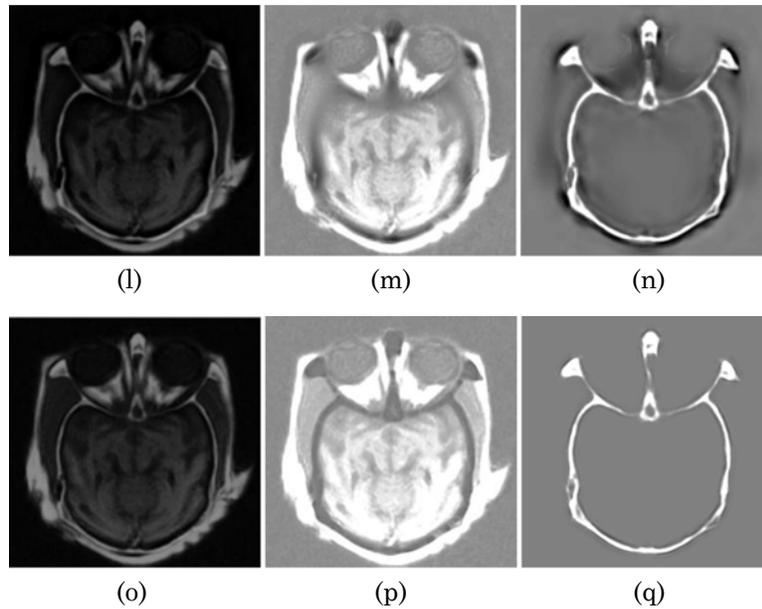
(i)



(j)



(k)



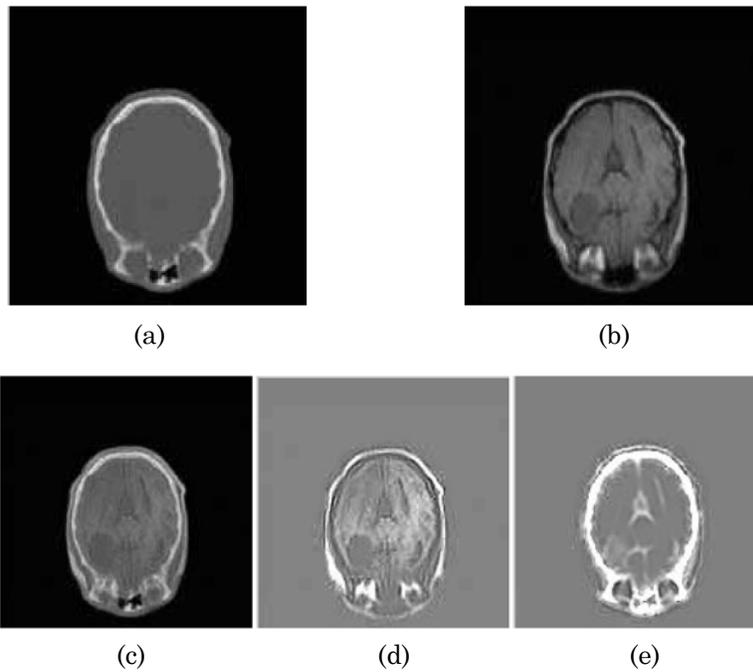
**Figure 3.** The fusion effects of each method. Figure 3(a) and 3(b) are the CT and MRI medical image. Figure 3(c), (f), (i), (l), (o) are the fusion images by using method in [4, 5, 7, 8] and our method. And Figure 3 (d, e), (g, h), (j, k), (m, n), (p, q) are difference images (fused images minus the Figure 3 (a) and (b)).

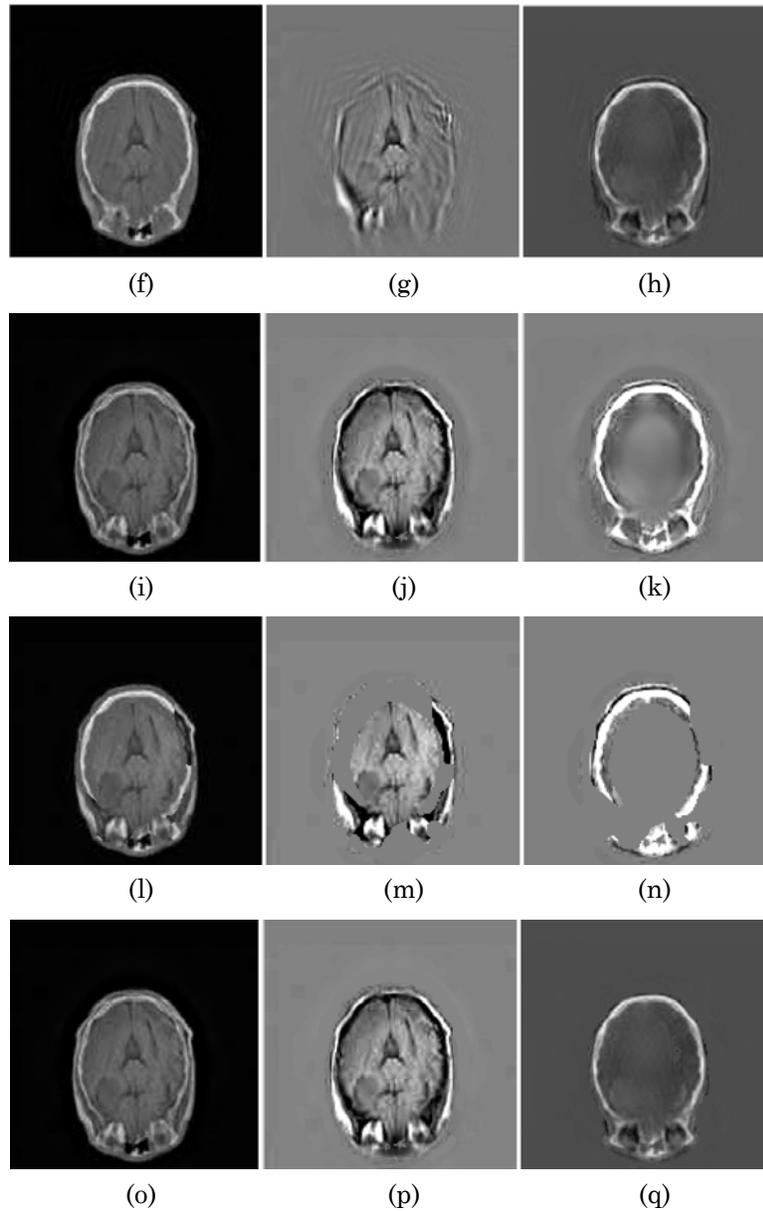
Comparing the fusion images of each algorithm and the different images are obtained by each method minus Figure 3(a) and 3(b), respectively, we can see our algorithm has better visual appearance and our algorithm preserves more textures information of source images. Besides the subjective visual appearance, four objective criteria mentioned above is use to investigate the performance of each method. As shown in Table 1, we can see that our algorithm has the highest performance in the  $Q^{AB/F}$ , MI, and SF. What's more, our algorithm has the fastest running speed. So, it is a kind of good medical image fusion algorithms. There is more medical test images are shown in Figure 4. These test images come from the web of "<http://www.imagefusion.org/>".

**Table 1.** Objective criterion in the image fusion with different methods

Fusion method	$Q^{AB/F}$	MI	SF	Time(s)
Method in [4]	0.5901	1.6195	9.1569	29.56
Method in [5]	0.5254	1.1221	8.7962	218.68
Method in [7]	0.7248	2.6951	8.8198	41.07
Method in [8]	0.7799	2.4216	8.9923	60.58
<b>Ours</b>	<b>0.7885</b>	<b>4.9850</b>	<b>9.4430</b>	<b>15.66</b>

Figure 4(a) and 4(b) are the next classical medical fusion images. The size of these two images both are  $128 \times 128$ . The methods proposed in [4, 5, 7, 8] and our method are applied to fuse these image, respectively. The fused images and difference images (fused images minus the source image) are shown in Figure 4(c)-4(q).





**Figure 4.** The fusion effects of each method of next test images. Figure 4(a) and 4(b) are the CT and MRI medical image. Figure 4(c), (f), (i), (l), (o) are the fusion images by using method in [4, 5, 7, 8] and our method. And Figure 4 (d, e), (g, h), (j, k), (m, n), (p, q) are difference images (fused images minus the Figure 4 (a) and (b)).

Comparing the fusion images of each algorithm and the different images are obtained by each method minus Figure 4(a) and 4(b), respectively, we can see our algorithm has better visual appearance and our algorithm preserves more textures information of source images. Besides the subjective visual appearance, four objective criteria mentioned above is use to investigate the performance of each method. As shown in Table 2, we can see that our algorithm has the highest performance in the  $Q^{AB/F}$ , MI, and SF. What's more, our algorithm has the fastest running speed.

**Table 2.** Objective criterion in the image fusion with different methods

Fusion method	$Q^{AB/F}$	MI	SF	Time(s)
Method in [4]	0.5920	3.8341	20.3673	17.23
Method in [5]	0.6126	3.0830	18.9718	109.57
Method in [7]	0.6994	3.9715	20.8178	20.98
Method in [8]	0.6789	3.0122	18.7314	31.09
<b>Ours</b>	<b>0.7555</b>	<b>4.3905</b>	<b>22.5345</b>	<b>9.56</b>

In order to repeat the experiments in this article conveniently, the code of this algorithm can be download from the web site of “[https://www.researchgate.net/publication/263414401\\_Medical\\_image\\_fusion\\_based\\_on\\_nonsampled\\_direction\\_complex\\_wavelet\\_transform?ev=prf\\_pub](https://www.researchgate.net/publication/263414401_Medical_image_fusion_based_on_nonsampled_direction_complex_wavelet_transform?ev=prf_pub)”.

## 5. Conclusion

We present a medical image fusion algorithm based on NSDFB-DTCWT transform. Firstly, the algorithm increases the decomposition low-frequency sub-bands coefficients of image by NSDFB-DTCWT. So, the structure and textures of the medical image information sufficiently are retained by using simple image fusion rule (maximum of the absolute value of coefficients). This construction not only improved fusion effect

but also simplify the complexity of calculation in fusion algorithm. Experimental results show that the method in the visual effects are superior and objective evaluation is better than image fusion based on wavelet, CT and NCST.

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