Pulse Coupled Neural Network-Based Multimodal Medical Image Fusion via Guided Filtering and WSEML in NSCT Domain

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Abstract: Multimodal medical image fusion aims to fuse images with complementary multisource information. In this paper, we propose a novel multimodal medical image fusion method using pulse coupled neural network (PCNN) and a weighted sum of eight-neighborhood-based modified Laplacian (WSEML) integrating guided image filtering (GIF) in non-subsampled contourlet transform (NSCT) domain. Firstly, the source images are decomposed by NSCT, several low- and high-frequency sub-bands are generated. Secondly, the PCNN-based fusion rule is used to process the low-frequency components, and the GIF-WSEML fusion model is used to process the high-frequency components. Finally, the fused image is obtained by integrating the fused low- and high-frequency sub-bands. The experimental results demonstrate that the proposed method can achieve better performance in terms of multimodal medical image fusion. The proposed algorithm also has obvious advantages in objective evaluation indexes VIFF, Q(W), API, SD, EN and time consumption.

Keywords: multimodal medical image; image fusion; PCNN; WSEML; GIF; NSCT

1. Introduction

In recent years, numerous medical image processing algorithms are being extensively used for visualizing complementary information. Medical image fusion is a very effective technique in combining the important information obtained from the multimodal images into one single composite image and enhance the diagnostic accuracy [1,2]. Medical images can be divided into the following categories: Computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), single-photon emission CT (SPECT) etc. Usually, there is no single imaging method that can reflect the complete tissue information; medical image fusion technology can retain the diagnostic information of input image to the maximum extent [3,4]. Figure 1 shows the example of image fusion, it involves not only medicine, but also a multifocus image and remote sensing image. In this paper, we mainly discuss the application of multimodal medical image fusion.

At present, a lot of image fusion techniques have been proposed by the researchers, and these image fusion methods are broadly categorized as spatial domain and transform domain [5,6]. The spatial domain-based image fusion methods have high computational efficiency, but these methods suffer from poor contrast and spatial localization [7,8]. In terms of technical development, many multiscale transform decomposition methods have been introduced to design an effective platform that provide better localization of an image contour and texture details [9]. These transforms include the discrete wavelet transform (DWT) [10], stationary wavelet transform (SWT) [11], dual-tree complex wavelet transform (DTCWT) [12], curvelet transform (CVT) [13], contourlet transform (CNT) [14], surfacelet transform [15], non-subsampled contourlet transform (NSCT) [16], shearlet transform (ST) [17], non-subsampled shearlet transform (NSST) [18], adjustable non-subsampled shearlet transform (ANSST) [19] etc. Iqbal et al. [20] proposed a novel multifocus image fusion scheme utilizing discrete wavelet transform and guided image filtering, which can...
provide outperformance fusion results both on qualitative and quantitative comparisons. Wang et al. [21] introduced a technique for multifocus image fusion based on discrete wavelet transform and convolutional neural network (CNN), leading to better fusion results than traditional DWT-based fusion algorithm. DTCWT is an extension of DWT and has translation invariance. Aishwarya et al. [22] proposed an image fusion method utilizing DTCWT and adaptive combined clustered dictionary, leading to good performance than the conventional multiscale transform-based algorithms and the state-of-the-art sparse representation-based algorithms.

Due to the limited ability in capturing directional information in two-dimensional space about the wavelets based methods, most wavelet transforms cannot generate an optimal representation for images. In order to address the aforementioned problem, a series of multi-scale geometric analysis (MGA) theory including curvelet, contourlet and shearlet have been introduced by the scientist, these methods accelerate the development of image fusion technology. Mao et al. [23] proposed an image fusion technique based on curvelet transform and sparse representation. Chen et al. [24] introduced an approach for multi-source optical remote sensing image fusion based on principal component analysis and curvelet transform. Li et al. [25] introduced the non-subsampled contourlet transform into the medical image fusion based on fuzzy entropy and regional energy. Wu et al. [26] conducted another NSCT-based work using pulse coupled neural network (PCNN) for infrared and visible image fusion. Li et al. [27] proposed an image fusion scheme based on parameter-adaptive pulse coupled neural network (PAPCNN) and improved sum-modified-laplacian (ISML) in non-subsampled shearlet transform (NSST) domain, leading to a good fusion performance.

Figure 1. The example of image fusion.
In recent years, the sparse representation-based, convolutional neural network-based, edge-preserving filter-based techniques also achieve successfully in the field of image fusion. Xing et al. [28] proposed an image fusion method based on Taylor expansion theory and convolutional sparse representation with gradient penalties scheme. Liu et al. [29] introduced an adaptive sparse representation (ASR) for multimodal image fusion and denoising. Liu et al. [30] proposed an image fusion technique using deep convolutional neural network (DCNN), leading to state-of-the-art image fusion performance in terms of visual quality and objective assessment. Li et al. [31] introduced the guided image filtering for image fusion (GFF), and the calculation efficiency is relatively high. The main image fusion models mentioned above can be summarized as shown in Table 1.

**Table 1.** The classifications and methods of main image fusion models.

| Categories                  | Methods                                      |
|-----------------------------|----------------------------------------------|
| Multiscale transform        | discrete wavelet transform (DWT) [10],      |
| decomposition               | stationary wavelet transform (SWT) [11],    |
|                             | dual-tree complex wavelet transform (DTCWT) [12], |
|                             | curvelet transform (CVT) [13],              |
|                             | contourlet transform (CNT) [14],            |
|                             | surfacelet transform [15],                  |
|                             | non-subsampled contourlet transform (NSCT) [16], |
|                             | shearer transform (ST) [17],                |
|                             | nonsubsampled shearer transform (NSST) [18], |
|                             | adjustable non-subsampled shearer transform (ANSST) [19] |
| Sparse representation       | convolutional sparse representation [28],   |
|                             | adaptive sparse representation (ASR) [29]   |
| Deep learning               | deep convolutional neural network (DCNN) [30] |
| Edge-preserving filter       | guided image filtering [31]                 |

The image fusion methods, based on transform domain, mainly use different energy functions to construct the weight of the source image for image fusion. Although the details of each source image can be well-preserved, the space continuity of the high- and low-frequency coefficients in the transform domain is often not considered, the fused image will introduce artificial texture, which will affect the image fusion effect. In this paper, a novel fusion model with pulse coupled neural network (PCNN) and weighted sum of eight-neighborhood-based modified Laplacian (WSEML) in NSCT domain is proposed for multimodal medical image fusion. The guided filtering is introduced to enhance the spatial continuity of the image, and then the corresponding artificial texture is suppressed and the gray level of the fused image is enhanced. The contributions of the proposed framework can be summarized as follows: (1) The multiscale NSCT decomposition is used to decompose the input source images into low- and high-frequency components; (2) the PCNN is adopted to fuse the low-frequency components, and the WSEML integrating guided image filtering is utilized to fuse the high-frequency components. The guided image filtering is a good edge-preserving filter, the proposed model can efficiently capture the spatial information and suppress noise; (3) the effectiveness of the proposed work is authenticated utilizing the extensive experimental fusion results and comparisons with the state-of-the-art image fusion algorithms.

The rest of this work is organized as follows. Preliminaries is briefly reviewed in Section 2. The proposed fusion algorithm is illustrated in Section 3. The experimental results and discussions are shown in Section 4. The conclusions are presented in Section 5.

2. Preliminaries

2.1. Non-Subsampled Contourlet Transform

The non-subsampled contourlet transform (NSCT) is an improved model of contourlet, NSCT adopts the multiscale, multidirectional analysis and shift-invariance. It is applied for image decomposition into one low-frequency and several high-frequency sub-bands. The decomposition model utilizes non-subsampled pyramid (NSP) to generate low-frequency
and high-frequency components and then the non-subsampled directional filter bank (NSDFB) is adopted to generate several sub-image components [32]. The overview of NSCT is depicted in Figure 2. NSCT is recognized as an effective method for image fusion [25,26], and it is selected as the multiscale transform for proposed fusion algorithm in this paper.

![Figure 2. The overview of NSCT [32]. (a) Non-subsampled filter bank structure; (b) Idealized frequency partitioning.](image)

2.2. Pulse Coupled Neural Network

Pulse coupled neural network (PCNN) is a feedback network, and it is widely used in the field of image fusion. In particular, it is reasonable to apply the PCNN model to merge the low-frequency components generated by the NSCT. The PCNN model is described as follows [16]:

$$F_{ij}(n) = S_{ij}$$  \(1\)

$$L_{ij}(n) = e^{-\alpha L} L_{ij}(n-1) + V_L \sum_{pq} W_{ij,pq} Y_{ij,pq}(n-1)$$  \(2\)

$$U_{ij}(n) = F_{ij}(n) \ast (1 + \beta L_{ij}(n))$$  \(3\)

$$\theta_{ij}(n) = e^{-\alpha \theta} \theta_{ij}(n-1) + V_\theta Y_{ij}(n-1)$$  \(4\)

$$Y_{ij}(n) = \begin{cases} 1 & \text{if } U_{ij}(n) > \theta_{ij}(n) \\ 0 & \text{else} \end{cases}$$  \(5\)

$$T_{ij} = T_{ij}(n-1) + Y_{ij}(n)$$  \(6\)

where $F_{ij}$ shows the feeding input and $S_{ij}$ denotes the external input stimulus signal, the linking input $L_{ij}$ depicts the sum of neurons firing times in linking range, $W_{ij,pq}$ represents the synaptic gain strength, $\alpha_L$ denotes the decay constants, $V_L$ and $V_\theta$ present the amplitude gain, $\beta$ shows the linking strength, $U_{ij}$ is the total internal activity, $\theta_{ij}$ represents the threshold, $n$ is the iteration times, $Y_{ij}$ is the pulse output of PCNN, $T_{ij}$ denotes the firing times. Figure 3 shows the architecture of the PCNN model.
2.3. Guided Image Filter

Guided image filter is a linear filtering, we suppose that the filtering output image \( q \) is the linear transform of the guidance image \( I \) in a window \( \omega_k \) centered at the pixel \( k \) [33]:

\[
q_i = a_k I_i + b_k, \forall i \in \omega_k
\]

where \( \omega_k \) presents the square window of size \((2r+1) \times (2r+1)\). The linear coefficients \((a_k, b_k)\) are constant in the \( \omega_k \), and they could be estimated by minimizing the cost function in the window \( \omega_k \):

\[
E(a_k, b_k) = \sum_{i \in \omega_k} \left( (a_k I_i + b_k - p_i)^2 + \varepsilon a_k^2 \right)
\]

where \( \varepsilon \) represents the regularization parameter penalizing large \( a_k \). The linear coefficients \((a_k, b_k)\) can be calculated by the following:

\[
a_k = \frac{1}{|\omega|} \sum_{i \in \omega_k} I_i p_i - \mu_k \bar{p}_k
\]

\[
b_k = \bar{p}_k - a_k \mu_k
\]

where \( \mu_k \) and \( \sigma_k^2 \) denote the mean and variance of \( I \) in \( \omega_k \), \( |\omega| \) shows the number of pixels in \( \omega_k \), and \( \bar{p}_k \) represents the mean of \( p \) in \( \omega_k \), it can be calculated by the following:

\[
\bar{p}_k = \frac{1}{|\omega|} \sum_{i \in \omega_k} p_i
\]

In order to keep the \( q_i \) value unchanged in different windows, all the possible data of \((a_k, b_k)\) are first averaged, the filtering output can be computed by

\[
q_i = \frac{1}{|\omega|} \sum_{k \mid i \in \omega_k} (a_k I_i + b_k) = \bar{a}_i I_i + \bar{b}_i
\]

where \( \bar{a}_i \) and \( \bar{b}_i \) present the mean of \( a_k \) and \( b_k \), respectively; they can be computed by

\[
\bar{a}_i = \frac{1}{|\omega|} \sum_{k \mid i \in \omega_k} a_k
\]

\[
\bar{b}_i = \frac{1}{|\omega|} \sum_{k \mid i \in \omega_k} b_k
\]
In this work, the $G_{r,\varepsilon}(p, I)$ is utilized to denote the guided filtering operation, $r$ and $\varepsilon$ denote the parameters which control the size of filter kernel and blur extent, respectively. $p$ refers to the input image, and $I$ represents the guidance image. The guided image filter is used to process the high-frequency components generated by NSCT.

3. Proposed Fusion Method

3.1. Overview

The proposed multimodal medical image fusion algorithm in this work is shown in Figure 4. The input source images are assumed to be well registered with the size $256 \times 256$, the detailed image fusion approach consists of four parts, namely NSCT decomposition, low-frequency sub-bands fusion, high-frequency sub-bands fusion, and NSCT reconstruction.

![Figure 4. The schematic diagram of the proposed fusion method.](image-url)

3.2. Detailed Fusion Algorithm

**Step 1: NSCT decomposition**

Suppose the registered input source images $A$ and $B$ are decomposed by NSCT transform with $L$-level, and generate the corresponding decomposition low- and high-frequency sub-bands $\{L_A, L_B\}$ and $\{H_A^k, H_B^k\}$, respectively.
Step 2: Low-frequency sub-band fusion

The low-frequency sub-band contains the approximate information of the source images, in this section, the PCNN based fusion rule is applied to keep more useful information. According to the PCNN model described from Equations (1)–(6), the fusion rule is depicted in the following:

\[
D_F(i, j) = \begin{cases} 
1 & \text{if } T_{A_{ij}}(N) \geq T_{B_{ij}}(N) \\
0 & \text{else}
\end{cases}
\] (15)

\[
L_F(i, j) = \begin{cases} 
L_A(i, j) & \text{if } D_{ij}(N) = 1 \\
L_B(i, j) & \text{else}
\end{cases}
\] (16)

where \(T_{A_{ij}}(N)\) and \(T_{B_{ij}}(N)\) are the PCNN firing times, \(N\) presents the total number of iterations; \(D_{ij}\) represents the decision map, \(L_F(i, j)\) denotes the fused low-frequency sub-band.

Step 3: High-frequency sub-bands fusion

The high-frequency sub-bands contain the plentiful edge and texture detail information of the input images, in order to extract the details information, the weighted sum of eight-neighborhood-based modified Laplacian (WSEML) is adopted, and it is defined as follows [34]:

\[
WSEML_S(i, j) = \sum_{m=-r}^{r} \sum_{n=-r}^{r} W(m + r + 1, n + r + 1) \times \text{EML}_S(i + m, j + n)
\] (17)

\[
\text{EML}_S(i, j) = |2S(i, j) - S(i - 1, j) - S(i + 1, j)| \\
+ |2S(i, j) - S(i, j - 1) - S(i, j + 1)| \\
+ \frac{1}{\sqrt{2}} |2S(i, j) - S(i - 1, j - 1) - S(i + 1, j + 1)| \\
+ \frac{1}{\sqrt{2}} |2S(i, j) - S(i - 1, j + 1) - S(i + 1, j - 1)|
\] (18)

where \(S \in \{A, B\}\); \(W\) denotes the weighting matrix, and it can be calculated by the following:

\[
W = \frac{1}{16} \begin{bmatrix} 
1 & 2 & 1 \\
2 & 4 & 2 \\
1 & 2 & 1
\end{bmatrix}
\] (19)

For the high-frequency coefficients, the fusion rule based on WSEML is adopted, and then the two zero-value matrixes \(\text{map}A\) and \(\text{map}B\) are initialized, and the matrixes are computed by the following:

\[
\text{map}A(i, j) = \begin{cases} 
1 & \text{if } \text{WSEML}_{H_A^{k}}(i, j) \geq \text{WSEML}_{H_B^{k}}(i, j) \\
0 & \text{else}
\end{cases}
\] (20)

\[
\text{map}B(i, j) = 1 - \text{map}A(i, j)
\] (21)

In order to enhance the spatial continuity of the high-frequency coefficients, the guided filter on \(\text{map}A\) and \(\text{map}B\) is adopted, and the corresponding coefficients \(H_A^{k}\) and \(H_B^{k}\) are utilized as the guided images:

\[
\text{map}A = G_{r,s}(\text{map}A, H_A^{k})
\] (22)

\[
\text{map}B = G_{r,s}(\text{map}B, H_B^{k})
\] (23)
where \( \text{mapA} \) and \( \text{mapB} \) should be normalized, the fused high-frequency coefficients \( H_{F}^{ij}(i,j) \) can be generated by the following Equation:

\[
H_{F}^{ij}(i,j) = \text{mapA} \times H_{A}^{ij}(i,j) + \text{mapB} \times H_{B}^{ij}(i,j)
\]

**Step 4: NSCT reconstruction**

The final fused image is generated by performing inverse NSCT transform over the merged fusion sub-bands \( \{L_{F}, H_{F}^{ij}\} \).

### 3.3. Extension to Color Image Fusion

The proposed medical image fusion algorithm is extended to fuse the anatomical and functional image in this section. The anatomical image contains the CT and MRI, and the functional image usually denotes the PET and SPECT. When solving the gray image and color image fusion, the image color space conversion is adopted, in this paper, the RGB to YUV color space is used to compute the anatomical and functional image fusion work [34]. The framework of the anatomical and functional image fusion is shown in Figure 5.

![Figure 5. Process flow for the proposed algorithm for anatomical and functional image in YUV color space.](image)

### 4. Experimental Results and Discussions

#### 4.1. Experimental Setup

In this section, to explore the effectiveness of the proposed multimodal medical image fusion algorithm, we evaluate the method on the two public datasets [http://www.imagefusion.org](http://www.imagefusion.org) and [http://www.med.harvard.edu/AANLIB/home.html](http://www.med.harvard.edu/AANLIB/home.html) (accessed on 10 February 2021). Figure 6 shows the selected public gray source image fusion pairs, all the CT and MRI source images have the same size with 256 × 256. Figure 7 denotes the selected anatomical and functional (MRI-PET/SPECT) images with the size 256 × 256, and all the source images are pre-registered. In addition, eight state-of-the-art fusion approaches are used to compare with the proposed scheme, namely image fusion based on non-subsampled contourlet transform (NSCT) [16], image fusion using dual-tree complex wavelet transform (DTCWT) [12], guided image filtering for image fusion (GFF) [31], image fusion utilizing ratio of low-pass pyramid (RP) [13], image fusion via adaptive sparse representation (ASR) [29], deep convolutional neural network based image fusion (DCCNN) [30], image fusion using convolutional sparsity based morphological component analysis (CSMCA) [35], single-scale structural image decomposition (SSID) [36]. In this paper, the pyramid filter and directional filter with the parameters “9–7” and “pkva”; the NSCT decomposition level is 4, and the corresponding directions are 4, 4, 4, 4; the parameters of the PCNN is set as \( p \times q, a_{L} = 0.06931, a_{a} = 0.2, \beta = 3, V_{L} = 1.0, \).
\( V_\theta = 20, W = \begin{bmatrix}
0.707 & 1 & 0.707 \\
1 & 0 & 1 \\
0.707 & 1 & 0.707 
\end{bmatrix} \), and the iterative number is \( N = 200 \); the parameters \( r \) and \( \varepsilon \) of guided image filter are set as 3 and 1, respectively. For the parameters in the comparison algorithms, corresponding parameter values are as described in the original papers proposed by the scholars. Table 2 summarizes the tested algorithms and the parameter setup. All of the experiments run in win7, MATLAB R2018b software. The hardware is Intel(R) Core(TM) i5-2520M CUP (2.50 GHz) and 12-GB memory.

Figure 6. Test gray medical images.

Figure 7. Test anatomical and functional images.
Table 2. All tested algorithms and the parameter settings.

| Methods | Parameter Setting |
|---------|-------------------|
| NSCT [16] | PCNN is set as $p \times q$, $a_L = 0.06931$, $a_B = 0.2$, $\beta = 0.2$, $V_L = 1.0$, $V_B = 20$, $W = \begin{bmatrix} 0.707 & 1 & 0.707 \\ 1 & 0 & 1 \\ 0.707 & 1 & 0.707 \end{bmatrix}$, and $N = 200$; the NSCT decomposition direction numbers are $[4, 4, 4, 4]$. |
| DTCWT [12] | $L = 4$; $r_1 = 45$, $\epsilon_1 = 0.3$, $r_2 = 7$, $\epsilon_2 = 10^{-6}$ |
| GFF [31] | $L = 4$; dictionary size: 256, $\epsilon = 0.1$, $C = 1.15$, $\sigma = 0$, the number of sub-dictionaries: 7 |
| RP [13] | patch size: $16 \times 16$, convolutional layer: kernel size $= 3 \times 3$, stride $= 1$, max-pooling layer: kernel size $= 2 \times 2$, stride $= 2$ |
| DCNN [30] | $L = 6$, $\lambda_c = \lambda_t = \max(0.6 - 0.1 \times i, 0.005)$, $i \in [1, L]$ |
| CSMCA [35] | $r = 15$ |
| SSID [36] | $r = 15$ |
| Proposed | PCNN is set as $p \times q$, $a_L = 0.06931$, $a_B = 0.2$, $\beta = 3$, $V_L = 1.0$, $V_B = 20$, $W = \begin{bmatrix} 0.707 & 1 & 0.707 \\ 1 & 0 & 1 \\ 0.707 & 1 & 0.707 \end{bmatrix}$, and $N = 200$; the NSCT decomposition direction numbers are $[4, 4, 4, 4]$, $r = 3$, $\epsilon = 1$. |

Notes: NSCT (non-subsampled contourlet transform), DTCWT (dual-tree complex wavelet transform), GFF (guided image filtering for image fusion), RP (ratio of low-pass pyramid), ASR (adaptive sparse representation), DCNN (deep convolutional neural network), CSMCA (convolutional sparsity based morphological component analysis), SSID (single-scale structural image decomposition).

The proposed medical image fusion technique is evaluated and compared with other classical fusion algorithms by qualitative and quantitative analyses. In terms of qualitative analysis, it is based on human visual system such as image details, image contrast and image brightness etc. As for quantitative analysis, multiple evaluation metrics are selected to assess the proposed fusion algorithm and the comparison fusion algorithms, which include the visual information fidelity (VIFF) [37–41], weighted fusion quality index ($Q_W$) [42,43], average pixel intensity (API) [44], standard deviation (SD) [44], entropy (EN) [44–48] and time (seconds). VIFF measures the visual information fidelity of the fused image by computing the distortion of the images, a larger VIFF means the fused image has higher visual information fidelity; the $Q_W$ addresses the distortions of coefficient correlation, illumination and contrast between the source images and fused image, a larger $Q_W$ means less distortion of image quality; API measures an index of contrast, a larger API reflects the fused image has higher contrast; SD measures the amount of information contained in the fused image from the perspective of statistics and reflects the overall contrast, a larger SD reflects the fused image contains more information and higher contrast; the computation of EN value is based on information theory, and it measures the amount of information in the fusion image, a larger EN means the fused image contains more information. The low computation time shows that the algorithm is efficient. Among the examined quantitative metrics, VIFF and $Q_W$ are reference-based metrics, while API, SD and EN are no-reference evaluation metrics. The fusion method takes the anatomical or functional image as the reference, it is easy to introduce the interference information from the source images into the fusion image. In order to comprehensively evaluate the fusion performance from different perspectives, this study uses reference-based and no-reference-based indicators. The corresponding fusion results and metrics data as shown in Figures 8–12 and Tables 3–7.
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4.2. Comparison of Gray Image Fusion

Figures 8–10 represent the gray medical image fusion results generated by different image fusion approaches. Figure 8 depicts the fused results of the methods on the first group gray medical images. Figure 9 presents the fusion results of the algorithms on the second group gray medical images. Figure 10 shows the fused results of the methods on the other gray medical images.

Figure 8. Fusion results of the first group gray medical images. (a) NSCT; (b) DTCWT; (c) GFF; (d) RP; (e) ASR; (f) DCNN; (g) CSMCA; (h) SSID; (i) Proposed method.
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**Figure 8.** Fusion results of the first group gray medical images. (a) NSCT; (b) DTCWT; (c) GFF; (d) RP; (e) ASR; (f) DCNN; (g) CSMCA; (h) SSID; (i) Proposed method.

**Figure 9.** Fusion results of the second group gray medical images. (a) NSCT; (b) DTCWT; (c) GFF; (d) RP; (e) ASR; (f) DCNN; (g) CSMCA; (h) SSID; (i) Proposed method.
Figure 10. Simulation results of other seven groups of gray medical images in Figure 6. From top to bottom, the fusion results of NSCT, DTCWT, GFF, RP, ASR, DCNN, CSMCA, SSID and proposed method are in turn.
Table 5. Average objective assessment of different fusion methods on the nine groups gray medical images in Figure 6.

| Algorithm | VIFF Q | W API | SD | EN | Time/s |
|-----------|--------|-------|----|----|--------|
| NSCT      | 0.5210 | 0.7761| 59.8996| 65.1086| 6.1218 |
| DTCWT     | 0.5181 | 0.7713| 54.4182| 59.9131| 5.7897 |
| GFF       | 0.5095 | 0.7813| 60.0666| 62.8036| 6.0636 |
| RP        | 0.3701 | 0.5758| 58.8046| 64.2301| 5.6415 |
| ASR       | 0.4824 | 0.7584| 53.6929| 57.2958| 5.3715 |
| DCNN      | 0.5439 | 0.7674| 65.3528| 73.7230| 5.1390 |
| CSMCA     | 0.5473 | 0.7822| 56.8599| 63.2075| 5.4745 |
| SSID      | 0.5970 | 0.7934| 66.2517| 70.0540| 5.6540 |
| Proposed  | 0.6121 | 0.8072| 70.5363| 74.2915| 5.9685 |

4.3. Comparison of Anatomical and Functional Image Fusion

In this section, nine groups of color medical images (MRI-PET/SPECT) are used to assess the fused results of the proposed fusion technique, and the corresponding comparative analysis is given. The typical MRI-PET fusion results of the techniques are given in Figure 11. From Figure 11, we can denote that the fused images such as Figure 11a–c,f generated by the NSCT, DTCWT, GFF, and DCNN algorithms, respectively, suffer from color distortion. Figure 11d–e are the fusion results computed by the RP and ASR methods, respectively; it can be clearly denoted that the fused results still exist color distortion, but the image contrast and brightness have improved. The fused image computed by the CSMCA is shown in Figure 11g, and the artificial textures are appeared, the fusion effects are undesirable. The fused images calculated by SSID and the proposed methods are depicted in Figure 11h,i, respectively, the two fused images are similar, but the proposed method has a better fusion performance and higher brightness. Figure 12 shows the fused results of different algorithms on the other eight groups of anatomical and functional images.

Figure 11. Fusion results of the first group anatomical and functional images. (a) NSCT; (b) DTCWT; (c) GFF; (d) RP; (e) ASR; (f) DCNN; (g) CSMCA; (h) SSID; (i) Proposed method.
Figure 11. Fusion results of the first group anatomical and functional images. (a) NSCT; (b) DTCWT; (c) GFF; (d) RP; (e) ASR; (f) DCNN; (g) CSMCA; (h) SSID; (i) Proposed method.

Figure 12. Simulation results of other eight groups of anatomical and functional images in Figure 7. From top to bottom, the fusion results of NSCT, DTCWT, GFF, RP, ASR, DCNN, CSMCA, SSID and proposed method are in turn.

Table 3. Objective assessment of different fusion methods on the first group gray images.

| Method  | VIFF | QW   | API   | SD    | EN    | Time/s |
|---------|------|------|-------|-------|-------|--------|
| NSCT    | 0.3440 | 0.7833 | 40.3719 | 49.9211 | 6.6284 | 23.3362 |
| DTCWT   | 0.3747 | 0.7481 | 32.5113 | 42.9503 | 6.2258 | 0.2269 |
| GFF     | 0.4863 | 0.8337 | 50.1930 | 53.7113 | 6.7920 | 0.2579 |
| RP      | 0.2256 | 0.5289 | 36.4669 | 51.5819 | 6.0500 | 0.2034 |
| ASR     | 0.3744 | 0.7526 | 31.5150 | 40.0483 | 6.1778 | 91.1108 |
| DCNN    | 0.2398 | 0.6949 | 22.3834 | 52.2447 | 3.4737 | 75.3303 |
| CSMCA   | 0.4752 | 0.8030 | 37.2620 | 50.7438 | 6.3268 | 200.6023 |
| SSID    | 0.4423 | 0.7988 | 51.2897 | 52.4270 | 6.6580 | 0.1608 |
| Proposed| 0.4594 | 0.8438 | 53.2905 | 55.1511 | 6.8000 | 17.9221 |
Table 4. Objective assessment of different fusion methods on the second group gray images.

| Method | VIFF | Qw  | API  | SD   | EN   | Time/s |
|--------|------|-----|------|------|------|--------|
| NSCT   | 0.4728 | 0.8324 | 56.2619 | 69.6178 | 5.2291 | 22.4744 |
| DTCWT  | 0.4830 | 0.8326 | 52.1862 | 65.5521 | 4.9310 | 0.1799  |
| GFF    | 0.4850 | 0.8448 | 54.5311 | 65.9081 | 5.3836 | 0.2404  |
| RP     | 0.3582 | 0.5464 | 55.5456 | 70.0442 | 4.5744 | 0.1278  |
| ASR    | 0.4680 | 0.8164 | 51.5346 | 63.9370 | 4.1560 | 87.0228 |
| DCNN   | 0.4638 | 0.8279 | 60.4476 | 74.8379 | 4.5250 | 78.8741 |
| CSMCA  | 0.4940 | 0.8444 | 53.2322 | 67.4899 | 4.3896 | 205.1055|
| SSID   | 0.5122 | 0.8426 | 55.8888 | 70.3751 | 4.5738 | 0.0721  |
| Proposed | 0.5151 | 0.8492 | 60.6443 | 75.1231 | 5.0524 | 18.5094 |

Table 5. Average objective assessment of different fusion methods on the nine groups gray medical images in Figure 6.

| Method | VIFF | Qw  | API  | SD   | EN   | Time/s |
|--------|------|-----|------|------|------|--------|
| NSCT   | 0.5210 | 0.7761 | 59.8996 | 65.1086 | 6.1218 | 23.7192 |
| DTCWT  | 0.5181 | 0.7713 | 54.4182 | 59.9131 | 5.7897 | 0.1778  |
| GFF    | 0.5095 | 0.7813 | 60.0666 | 62.8036 | 6.0636 | 0.2568  |
| RP     | 0.3701 | 0.5758 | 58.8046 | 64.2301 | 5.6415 | 0.1428  |
| ASR    | 0.4824 | 0.7584 | 53.6929 | 57.3985 | 5.4375 | 106.4738|
| DCNN   | 0.5439 | 0.7674 | 65.3528 | 73.7230 | 5.1390 | 80.0550 |
| CSMCA  | 0.5473 | 0.7822 | 56.8899 | 63.2075 | 5.4745 | 199.1734|
| SSID   | 0.5970 | 0.7934 | 66.2517 | 70.0540 | 5.6540 | 0.0848  |
| Proposed | 0.6121 | 0.8072 | 70.5363 | 74.2915 | 5.9685 | 19.0577 |

Table 6. Objective assessment of different fusion methods on the first group anatomical and functional images.

| Method | VIFF | Qw  | API  | SD   | EN   | Time/s |
|--------|------|-----|------|------|------|--------|
| NSCT   | 0.2651 | 0.7986 | 43.1364 | 64.8996 | 4.7648 | 28.2017 |
| DTCWT  | 0.5901 | 0.8250 | 43.4533 | 62.9923 | 4.6493 | 0.1937  |
| GFF    | 0.1899 | 0.8075 | 33.8746 | 64.0359 | 4.4073 | 0.2377  |
| RP     | 0.8443 | 0.8471 | 45.8674 | 68.7038 | 4.7289 | 0.1570  |
| ASR    | 0.3150 | 0.7602 | 42.9496 | 61.1235 | 4.1997 | 85.6910 |
| DCNN   | 0.2016 | 0.8049 | 36.4412 | 63.0764 | 4.5451 | 80.3691 |
| CSMCA  | 0.3088 | 0.7926 | 44.4419 | 63.9466 | 4.5383 | 193.1375|
| SSID   | 0.3675 | 0.6837 | 53.5451 | 74.4686 | 4.6702 | 0.0862  |
| Proposed | 0.3905 | 0.7737 | 57.7310 | 80.6245 | 4.9169 | 20.5294 |

Table 7. Average objective assessment of different fusion methods on the nine groups anatomical and functional images in Figure 7.

| Method | VIFF | Qw  | API  | SD   | EN   | Time/s |
|--------|------|-----|------|------|------|--------|
| NSCT   | 0.5016 | 0.8946 | 39.8883 | 56.0495 | 4.7101 | 26.5087 |
| DTCWT  | 0.7396 | 0.9034 | 35.7573 | 50.1217 | 4.7462 | 0.2026  |
| GFF    | 0.4947 | 0.8995 | 38.8141 | 55.1386 | 4.6584 | 0.2475  |
| RP     | 0.6223 | 0.7878 | 38.4400 | 53.6370 | 4.6522 | 0.1562  |
| ASR    | 0.4688 | 0.8342 | 35.2421 | 48.2889 | 4.3736 | 92.3286 |
| DCNN   | 0.4952 | 0.8936 | 39.6507 | 56.7982 | 4.6641 | 79.5171 |
| CSMCA  | 0.3801 | 0.6798 | 29.8909 | 42.2079 | 4.1895 | 186.4474|
| SSID   | 0.5425 | 0.8690 | 41.1085 | 56.0659 | 4.6606 | 0.0828  |
| Proposed | 0.5484 | 0.8968 | 43.7113 | 59.6273 | 4.8847 | 19.3064 |
4.2. Comparison of Gray Image Fusion

Figures 8–10 represent the gray medical image fusion results generated by different image fusion approaches. Figure 8 depicts the fused results of the methods on the first group gray medical images. Figure 9 presents the fusion results of the algorithms on the second group gray medical images. Figure 10 shows the fused results of the methods on other gray medical images.

With regard to the visual performance, the edge information in Subfigure (a) of Figures 8 and 9 denotes that the fused images of NSCT have lost some details of MRI images, and the results have some noise, which affects the doctor’s observation. From the Subfigure (b) of Figures 8 and 9 generated by the DTCWT method have the low contrast and brightness. We can denote the blocking artifacts are generated by GFF algorithm as shown in Subfigure (c) of Figures 8 and 9, due to the guided image filtering is a non-linear filter, it needs the same or better guidance image to implement the smoothing process. The fused images calculated by RP and DCNN schemes as shown in Subfigures (d) and (f) of Figures 8 and 9, respectively, and the results produce certain kinds of distortions, especially the Figure 8f obtained by DCNN, almost all the information of MRI image is lost in the fusion image. ASR algorithm can generate the block effect and the gradient contrast is poor, which could be denoted from Subfigure (e) of Figures 8 and 9. It can be seen from Subfigure (g) of Figures 8 and 9 that the fused results computed by CSMCA approach lead to information loss. The fusion results calculated by the SSID and proposed techniques are relatively high-quality, and they are depicted in Subfigures (h) and (i) of Figures 8 and 9, the results of the proposed method retain more image information and the brightness is higher.

In order to reduce the influence of individual subjective judgment on image fusion quality as far as possible, the objective evaluation indicators are introduced, and the corresponding index values are shown in Tables 3–5. From the Table 3, in terms of QW, API, SD and EN, the proposed approach generates superb performance, although the best data for VIFF and Time are generated by GFF and SSID, with 0.4863 and 0.1608, respectively. From the Table 4, we can see that the values of VIFF, QW, API and SD obtained by the proposed fusion scheme are the best, while the best data for EN and Time are generated by GFF and SSID, with 5.3836 and 0.0721, respectively. In order to analyze the universality of the fusion algorithms more objectively, we take the average values of the index data obtained from nine groups of gray medical images computed by the nine fusion methods, as shown in Table 5, in addition to the EN and Time values, the other four metric values obtained by the proposed algorithm are the best.

4.3. Comparison of Anatomical and Functional Image Fusion

In this section, nine groups of color medical images (MRI-PET/SPECT) are used to assess the fused results of the proposed fusion technique, and the corresponding comparative analysis is given. The typical MRI-PET fusion results of the techniques are given in Figure 11. From the Figure 11, we can denote that the fused images such as Figure 11a–c,f generated by the NSCT, DTCWT, GFF, and DCNN algorithms, respectively, suffer from color distortion. Figure 11d–e are the fusion results computed by the RP and ASR methods, respectively; it can be clearly denoted that the fused results still exist the color distortion, but the image contrast and brightness have improved. The fused image computed by the CSMCA is shown in Figure 11g, and the artificial textures are appeared, the fusion effects are undesirable. The fused images calculated by SSID and the proposed methods are depicted in Figure 11h,i, respectively, the two fused images are similar, but the proposed method has a better fusion performance and higher brightness. Figure 12 shows the fused results of different algorithms on the other eight groups of anatomical and functional images.

The quantitative assessments on the fused images of Figure 11 corresponding to the first group anatomical and functional images are tabulated in Table 6. We can see that the metrics data of API, SD and EN computed by the proposed algorithm are the best.
compared with other state-of-the-art fusion strategies, while the best data for VIFF, Q_w
and Time are computed by RP and SSID, with 0.8443, 0.8471 and 0.0806, respectively.

Here, the average of the six metrics calculated by the various fusion approaches on the
selected nine groups anatomical and functional images in Figure 7 are recorded, as shown
in Table 7. In contrast to the other fusion techniques, there is a remarkable enhancement on
the metrics API, SD and EN. The overall comparative analysis shows that the proposed
scheme works better in terms of anatomical and functional images fusion, demonstrating
its effectiveness.

From the anatomical-anatomical image fusion results and anatomical-functional im-
age fusion results aforementioned, the proposed algorithm has obvious advantages in
subjective and objective evaluations compared with other state-of-the-art fusion algorithms.
The PCNN fusion rule and GIF-WSEML fusion rule are used in the NSCT domain, the
combination of the two fusion models denotes better preservation of spatial and spectral
features. The fusion images can provide accurate location of defected tissues, and provide
meaningful quantitative explanation for clinical diagnosis. Given that there are many pa-
rameters in this algorithm, it needs continuous manual debugging to select the appropriate
values of parameters to achieve the optimal fusion effect.

5. Conclusions

In this paper, a practical multimodal medical image fusion algorithm based on PCNN
and GIF-WSEML in non-subsampled contourlet transform domain is introduced. For
sub-bands fusion, two different rules are adopted, the low-frequency sub-bands are fused
by PCNN model, and the weighted sum of eight-neighborhood-based modified Laplacian
integrating guided image filtering (GIF-WSEML) is used to merge the high-frequency sub-
bands. The nine groups of anatomical-anatomical images and nine groups of anatomical-
functional images are used to simulate by the proposed framework and other conventional
fusion approaches. The comparative experimental fusion results conducted on both gray
and color medical image datasets demonstrate that the proposed fusion algorithm has a
better performance with improved brightness and contrast of multimodal medical images,
and the objective metrics such as VIFF, Q_w, API, SD and EN computed by the proposed
method also have obvious advantages. Compared to DTCWT, GFF, RP and SSID, the time
consuming of the proposed method is high, so reducing the operation time and improving
the real-time performance of the algorithm are the problems we need to solve in the future.

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Abbreviations

| Abbreviation | Description |
|--------------|-------------|
| PCNN         | pulse coupled neural network |
| WSEML        | weighted sum of eight-neighborhood-based modified Laplacian |
| GIF          | guided image filtering |
| NSCT         | nonsubsampled contourlet transform |
| CT           | computed tomography |
| MRI          | magnetic resonance imaging |
PET positron emission tomography
SPECT single-photon emission CT
DWT discrete wavelet transform
SWT stationary wavelet transform
DTCWT dual-tree complex wavelet transform
CVT curvelet transform
CNT contourlet transform
ST shearlet transform
NSST nonsubsampled shearlet transform
ANSST adjustable nonsubsampled shearlet transform
CNN convolutional neural network
MGA multi-scale geometric analysis
PAPCNN parameter-adaptive pulse coupled neural network
ISML improved sum-modified-laplacian
DCNN deep convolutional neural network
GFF guided image filtering for image fusion
NSP nonsubsampled pyramid
NSDFB nonsubsampled directional filter bank
RP ratio of low-pass pyramid
ASR adaptive sparse representation
CSMCA convolutional sparsity based morphological component analysis
SSID single-scale structural image decomposition
VIFF visual information fidelity
QW weighted fusion quality index
API average pixel intensity
SD standard deviation
EN entropy

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