Research Article

Medical Image Fusion Based on Fast Finite Shearlet Transform and Sparse Representation

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Clinical diagnosis has high requirements for the visual effect of medical images. To obtain rich detail features and clear edges for fusion medical images, an image fusion algorithm FFST-SR-PCNN based on fast finite shearlet transform (FFST) and sparse representation is proposed, aiming at the problem of poor clarity of edge details that is conducive to maintaining the details of source image in current algorithms. Firstly, the source image is decomposed into low-frequency coefficients and high-frequency coefficients by FFST. Secondly, the K-SVD method is used to train the low-frequency coefficients to obtain the overcomplete dictionary $D$, and then the OMP algorithm sparsely encodes the low-frequency coefficients to complete the fusion of the low-frequency coefficients. Then, a high-frequency coefficient is applied to excite a pulse-coupled neural network, and the fusion coefficient of the high-frequency coefficient is selected according to the number of ignitions. Finally, the fused low-frequency coefficient and high-frequency coefficient are reconstructed into the fused medical image by FFST inverse transform. The experimental results show that the image fusion result of the proposed algorithm is about 35% higher than the comparison algorithms for the edge information transfer factor QAB/F index and has achieved good results in both subjective visual effects and objective evaluation indicators.

1. Introduction

With the development of imaging devices, different sensors can acquire different information from images of the same scenario [1–4]. In medicine, images of different modes are properly fused to make the source images complementary to each other and thus obtain more informative images [5, 6].

In recent years, the image fusion method based on multiscale geometric analysis has been widely used in the image processing due to its multiresolution characteristics [7]. The wavelet transform [8, 9] is the most typical multiscale analysis method, but it has only three (horizontal, vertical, and diagonal) directions when decomposing an image and thus cannot well represent a two-dimensional image with curve singularity or a high-dimensional function with surface singularity, and it is easy to produce pseudo-Gibbs phenomenon. To solve this problem, multiscale geometric analysis methods such as contourlet transform [10] and shearlet transform [11] have been proposed successively. They have good anisotropy and directional selectivity. Among them, the NSCT is the best one for the image fusion. NSCT has a translation invariance, and it can attenuate the Gibbs effect generated in various types of transformations in the past. But the amount of computational data is too large, the computational complexity is high, and the real-time performance is poor. Compared with NSCT, the shearlet transform [12] fusion algorithm has a more flexible structure, higher computational efficiency, and better fusion effect. However, it uses subsampled in the discretization process, thus it has no translation invariance and is easy to produce pseudo-Gibbs phenomenon near singular points during the image fusion. By cascading the non-subsampling pyramid filter and the shear filter, fast finite shearlet transform (FFST) [13] gets all the
advantages of the shearlet transform, avoids the subsampled process, and obtains translation invariance. However, FFST exhibits a problem: the low-frequency coefficients it decomposed are not sparse. Sparse representation (SR) can express the deeper structural characteristics among low-frequency coefficients and make a perfect approximation for the linear combination of a small number of atoms in the dictionary [14]. To extract the fine contour information from the edge of images, highlight the edge features, and get more abundant information, this paper proposed the FFST-SR-PCNN, a medical image fusion algorithm based on the fast finite shearlet transform (FFST) and sparse representation (SR).

2.2. FFST. The shearlet transform generated shearlet functions with different features by scaling, shearing, and translating basis functions. Image decomposition based on the shearlet transform included the following: (1) decompose images into low-frequency and high-frequency subbands at different scales with Laplacian pyramid algorithm; (2) directionally subdivide subbands of different scales with the shear filter to realize multiscale and multidirectional decomposition and to make the size of the decomposed subband images consistent with the source images [15].

To obtain a discrete shearlet transformation, this algorithm discretized the scaling, shearing, and translating parameters in formula (2):

\[ a_j := 2^{-2j} = \frac{1}{4^j}, \quad j = 0, \ldots, j_0 - 1, \]

\[ s_{jk} := k2^{-j}, \quad -2^j \leq k \leq 2^j, \]

\[ t_m := \frac{m}{N}, \quad m \in \mathbb{N}, \]

where \( \mathbb{N} = \{m_1, m_2\}; m_0 = 0, \ldots, N-1, \quad i = 1, 2 \) and \( j_0 \) represented the scale of decomposition; thus a discrete shearlet was obtained:

\[ \tilde{\psi}_{j,k,m} = \psi(A^{-1}_{j,k,m}(x - t_m)). \]

The expression of the frequency domain was

\[ \tilde{\psi}_{j,k,m}(\omega) = \tilde{\psi}(A_{j,k,m}^{-1} B_{j,k,m}^{-1} \omega) \exp(-2\pi i \langle \omega, t_m \rangle) \]

\[ = \tilde{\psi}_1(4^j \omega_1) \tilde{\psi}_2(\frac{2^j \omega_2}{\omega_1} + k) \exp(-\frac{2\pi i \langle \omega, t_m \rangle}{N}), \]

where

\[ \Omega := \{(w_1, w_2): w_1 = -\frac{N}{2}, \ldots, \frac{N}{2} - 1, \quad i = 1, 2\}. \]

To obtain the shearlets in the whole frequency domain, \( |k| = 2^j \) was defined at the intersection of the conical surfaces, and the sum of the shearlets was

\[ \tilde{\psi}^{h, v}_{j,k,m} = \tilde{\psi}^{h}_{j,k,m} + \tilde{\psi}^{v}_{j,k,m}. \]

Thus, the discrete shearlet can be expressed as

\[ \text{SH}(f)(j, k, m) = \begin{cases} \langle f, \phi_m \rangle, & \tau = 0, \\ \langle f, \tilde{\psi}^{h,v}_{j,k,m} \rangle, & \tau \in [h, v], \\ \langle f, \tilde{\psi}^{h, v}_{j,k,m} \rangle, & \tau = \times, |k| = 2^j, \end{cases} \]

where \( j = 0, \ldots, j_0 - 1, \quad -2^j \leq k \leq -1, \) and \( m \in \mathbb{N}. \)

The shearlet defined by formula (9) can be realized by a two-dimensional fast Fourier transform algorithm with high computational efficiency. Since FFST has no subsampled process, it owns translation invariance. FFST also has excellent localization characteristics and high directional sensitivity.
2.3. Sparse Representation. The basic idea of sparse representation is to represent or approximately represent any signal by the linear combination of a small number of nonzero atoms in a given dictionary [16]. If a signal can be represented or approximated by the linear combination of a small number of atoms in $D \in \mathbb{R}^{K \times N}$, then the mathematical model of sparse representation [14] can be obtained by the following formula:

$$\min_A \|A\|_0,$$

subject to $$\|X - DA\|_2^2 < \varepsilon,$$  \hspace{1cm} (10)

where dictionary $D = [d_1, d_2, \ldots, d_K] \in \mathbb{R}^{K \times N}$ is an overcomplete set; $A$ is the coefficient of the sparse representation of signal $X$; $\|A\|_0$ is the $L_0$ norm of $A$; and $\varepsilon$ is the margin of approximation error.

In FFST-SR-PCNN, first, the K singular value decomposition (K-SVD) method was used to train low-frequency coefficients and obtain the matrix $D$ of an overcomplete dictionary. Then, the orthogonal matching pursuit (OMP) optimization algorithm was used to approximate the original signal through the local optimal solution and estimate the coefficient of the sparse representation [17]. Finally, the sparse coefficients were fused according to image features adaptively.

With the complete dictionary $D \in \mathbb{R}^{K \times N}$, the objective function equation of the K-SVD algorithm can be written as follows:

$$\min_{D,a} \|X - Da\|_2^2,$$

subject to $\forall_{i} \|a_i\|_0 \leq T_0,$$  \hspace{1cm} (11)

where $T_0$ is the sparse representation of the maximum number of nonzero count in the coefficient, i.e., the maximum sparsity.

Formula (11) is an iterative process. First, suppose the dictionary $D$ is fixed, then use the orthogonal matching pursuit (OMP) algorithm to get the sparse matrix; next, fix the matrix and update the dictionary column by column, which means only the first atom in the dictionary is updated.

The fusion process of low-frequency coefficient based on sparse presentation is illustrated in Figure 2.

In Figure 2, $L_A$ and $L_B$ are low-frequency coefficients; $n \times n$ is the size of the sliding window.

2.4. Pulse-Coupled Neural Network. Pulse-coupled neural network (PCNN) can combine the input high-frequency coefficients with human visual characteristics to obtain detailed information such as texture, edge, and contour [18]. The mathematical expression of the simplified model is

$$\begin{align*}
F_{ij}[n] &= I_{ij}, \\
L_{ij}[n] &= \exp(-\alpha_L)L_{ij}[n-1] + V_L \sum_{k,l} W_{ijkl} Y_{ij}[n-1], \\
U_{ij}[n] &= F_{ij}[n](1 + \beta)L_{ij}[n], \\
\theta_{ij}[n] &= \exp(-\alpha_\theta)\theta_{ij}[n-1] + V_\theta Y_{ij}[n-1], \\
Y_{ij}[n-1] &= \begin{cases} 1, & U_{ij}[n] > \theta_{ij}[n], \\
0, & U_{ij}[n] \leq \theta_{ij}[n], 
\end{cases}
\end{align*}$$

where $n$ is the number of iterations; $I_{ij}$ is the stimulation signal; $Y_{ij}$ and $U_{ij}$ are the external input and the internal state, respectively; $F_{ij}$ is the feedback input; $L_{ij}$ is the link input; $W_{ijkl}$ is the connection weight coefficient between neurons; $\beta$, $\theta_{ij}$, and $\alpha_\theta$ are the link strength, the variable threshold input, and the time constant of variable threshold attenuation, respectively; and $V_L$ and $V_\theta$ are amplification coefficients of the link input and the threshold.

High-frequency coefficient fusion used a pixel as the neuronal feedback input to stimulate the simplified PCNN model. SF was

$$F_{ij} = SF_{ij} = \sqrt{RF_{ij}^2 + CF_{ij}^2},$$

where the window size was $3 \times 3$; $RF_{ij}$ and $CF_{ij}$ were

$$RF_{ij} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=2}^{N} [X(i, j) - X(i, j-1)]^2,$$

$$CF_{ij} = \frac{1}{M \times N} \sum_{i=2}^{M} \sum_{j=1}^{N} [X(i, j) - X(i-1, j)]^2.$$
It got ignition maps through PCNN ignition and selected fusion coefficients according to the number of ignition times.

3. Implementation of FFST-SR-PCNN

3.1. Rules of Low-Frequency Coefficient Fusion. The process was implemented as follows:

Step 1. Decompose the source images A and B with the registered size $M \times N$ by FFST to obtain the low-frequency coefficient and the high-frequency coefficient.

Step 2. Using a sliding window with a step size of one pixel $S$ and a size $n \times n$, the low-frequency coefficients $L_A$ and $L_B$ are subjected to block processing to obtain $(N + n - 1) \times (M + n - 1)$ image subblocks, and the image subblocks are converted into column vectors to obtain a sample training matrix $V_A$ and $V_B$.

Step 3. Do iterative operation for sample matrix with K-SVD and obtain overcomplete dictionary matrix $D$ of low-frequency efficient.

Step 4. Estimate the sparse coefficient of $V_A$ and $V_B$ with OMP algorithm and obtain sparse coefficient matrix $\alpha_A$ and $\alpha_B$. The $i$th column sparse coefficient matrix will be fused as follows.

Case 1. If the $L_1$ norm of $\alpha_A$ is larger than $L_1$ norm of $\alpha_B$, then fuse with equation (15):

$$\alpha_F^i = \begin{cases} \alpha_A^i + \frac{1}{2}\alpha_B^i, & \text{if } \alpha_A^i < \alpha_B^i, \alpha_A^i \cdot \alpha_B^i < 0, \\ \alpha_A^i, & \text{otherwise.} \end{cases}$$  \hspace{1cm} (15)

Case 2. If the $L_1$ norm of $\alpha_A$ is smaller than $L_1$ norm of $\alpha_B$, then fuse with equation (16):

$$\alpha_F^i = \begin{cases} \alpha_B^i + \frac{1}{2}\alpha_A^i, & \text{if } \alpha_A^i > \alpha_B^i, \alpha_A^i \cdot \alpha_B^i < 0, \\ \alpha_B^i, & \text{otherwise.} \end{cases}$$  \hspace{1cm} (16)

Case 3. If the $L_1$ norm of $\alpha_A$ is equal to $L_1$ norm of $\alpha_B$, then fuse with equation (17):

$$\alpha_F^i = \begin{cases} \alpha_A^i + \frac{1}{2}\alpha_B^i, & \text{if } \alpha_A^i > \alpha_B^i, \alpha_A^i \cdot \alpha_B^i < 0, \\ \alpha_A^i, & \text{if } \alpha_A^i < \alpha_B^i, \alpha_A^i \cdot \alpha_B^i < 0, \\ \frac{\alpha_A^i + \alpha_B^i}{2}, & \text{otherwise}, \end{cases}$$  \hspace{1cm} (17)

where $\alpha_A^i$ and $\alpha_B^i$ are the $i$th column sparse coefficient matrix of $\alpha_A$ and $\alpha_B$, respectively; $\alpha_F^i$ is the $i$th column fused sparse coefficient matrix.

Step 5. Multiply overcomplete dictionary matrix $D$ and fused sparse coefficient matrix $\alpha_F$. Fused sample training matrix $V_F$ is

$$V_F = D\alpha_F.$$  \hspace{1cm} (18)

Step 6. Turn the columns of $V_F$ into data subblocks, reconstruct data subblocks, and obtain low-frequency fusion coefficient.

3.2. Rules of High-Frequency Coefficient Fusion. The process was implemented as follows:

Step 1. Calculate the neighborhood spatial frequency SF$_A$ and SF$_B$ of the high-frequency coefficients $H_A$ and $H_B$ according to equation (13) and use it as the link strength values of the neurons.

Step 2. Initialization: $L_{ij}(0) = U_{ij}(0) = \theta_{ij}(0) = 0$. Now neurons are in off state, i.e., $Y_{ij}(0) = 0$ the resulting pulse is $O_{ij}(0) = 0$.

Step 3. Compute $L_{ij}[n]$, $U_{ij}[n]$, $\theta_{ij}[n]$ and $Y_{ij}[n]$ according to equation (12).

Step 4. Compare the output threshold (ignition frequency) of firing time at the pixels of fire mapping image $O_A$, $O_B$; the high-frequency fused coefficient $H_F(i, j)$ is
\[ H_e(i, j) = \begin{cases} H_A(i, j), & \text{if } O_A(i, j) > O_B(i, j), \\ H_B(i, j), & \text{if } O_A(i, j) < O_B(i, j), \\ \frac{H_A(i, j) + H_B(i, j)}{2}, & \text{if } O_A(i, j) = O_B(i, j). \end{cases} \] (19)

4. Experimental Results and Analysis

In order to verify the effectiveness of FFST-SR-PCNN, five representative algorithms were selected as the controls for medical image fusion experiments. Five indicators including spatial frequency (SF), average gradient (AG), mutual information (MI), edge information transfer factor QAB/F (high-weight evaluation indicator) [19–22], and running time (RT) were used to make objective evaluation. Comparing algorithm 1 was a fusion algorithm proposed in [23] for images based on PCNN. Comparing algorithm 2 was an improved fusion algorithm proposed in [24] for medical images based on NSCT and adaptive PCNN. Comparing algorithm 3 was a fusion algorithm proposed in [25] for medical images based on SR and neural network. Comparing algorithm 4 was a fusion algorithm proposed in [26] for multimode medical images based on NSCT and Log-Gabor energy. Comparing algorithm 5 was a fusion algorithm proposed in [27] for medical images based on non-subsampled Shearlet transform and parameter adaptive pulse-coupled neural network.

4.1. Gray Image Fusion Experiment. In this experiment, six pairs of brain images in different states were selected for fusion. The first three pairs are CT/MR-T2 images and the last three pairs are MR-T1/MR-T2 images. The resulting images fused by different algorithms are shown in Figures 3–8, and their objective quality evaluation indicators are listed in Tables 1–6.

According to Figures 3–8, comparing algorithm 1 gave poor performance compared to the source images in the presentation of detailed feature information and had horizontal and vertical blocking effects (Figures 3(c), 4(c), 5(c), 6(c), 7(c), and 8(c)). Comparing algorithm 2 gave poor performance compared to the source MR-T2 image in the presentation of detailed edge information and had blurry edge details (Figures 3(d), 4(d), 5(d), 6(d), 7(d), and 8(d)). Comparing algorithm 3 had low overall contrast and blurred edge details (Figures 3(e), 4(e), 5(e), 6(e), 7(e), and 8(e)). Comparing algorithm 4 had blurry edge details (Figures 3(f), 4(f), 5(f), 6(f), 7(f), and 8(f)). Comparing algorithm 5 had low contrast in the upper right corner (Figures 3(g), 4(g), 5(g), 6(g), 7(g), and 8(g)). FFST-SR-PCNN fully retained the feature information of the source images, without dark lines and low contrast (Figures 3(h), 4(h), 5(h), 6(h), 7(h), and 8(h)). From the evaluation indicators in Tables 1–6, FFST-SR-PCNN had better performance than the other five comparing algorithms on QAB/F by an average increase of 15.5%. FFST-SR-PCNN is not always the best one in each individual evaluation indicators, but it never ranked less than top three. It can be seen that the computational efficiency of FFST-SR-PCNN was lower than comparing algorithm 5 (average 34.8% lower), while higher than the other four
methods (average 34.6%, 65%, 63.7%, and 48.5% higher, respectively). This is because the number of iterations of the comparison algorithm 5 is relatively small, but its other indicators were not as good as FFST-SR-PCNN. Totally, FFST-SR-PCNN had the best effect and can provide better fused medical images with relative lower computing cost.

4.2. Color Image Fusion Experiment. In this experiment, six pairs of brain images in different states were selected for

Figure 4: CT/MR-T2 medical image fusion results. (a) CT original image. (b) MR-T2 original image. (c) Method 1. (d) Method 2. (e) Method 3. (f) Method 4. (g) Method 5. (h) FFST-SR-PCNN.

Figure 5: CT/MR-T2 medical image fusion results. (a) CT original image. (b) MR-T2 original image. (c) Method 1. (d) Method 2. (e) Method 3. (f) Method 4. (g) Method 5. (h) FFST-SR-PCNN.
The first three pairs are MR-T2/PET images and the last three pairs are MR-T2/SPECT images. The resulting images fused by different algorithms are shown in Figures 9–14, and their objective quality evaluation indicators are listed in Tables 7–12.

According to Figures 9–14, comparing algorithm 1 gave poor performance compared to the source image in the presentation of detailed feature information and had widespread blocking effects (Figures 9(c), 10(c), 11(c), 12(c), 13(c), and 14(c)). Comparing algorithm 2 retained most
feature information from the source images, but the fused image had low overall contrast (Figures 9(d), 10(d), 11(d), 12(d), 13(d), and 14(d)). Comparing algorithm 3 had blurred edge contours compared to the source image (Figures 9(e), 10(e), 11(e), 12(e), 13(e), and 14(e)). Comparing algorithm 4 retained most of the feature information from the source image, but the edge contours are blurred (Figures 9(f), 10(f), 11(f), 12(f), 13(f), and 14(f)). Comparing algorithm 5 has clearer details than the other four algorithms (method 1 to method 4), but its contrast is still somewhat low (Figures 9(g), 10(g), 11(g), 12(g), 13(g), and 14(g)). The FFST-SR-PCNN method fully retained the feature information from the source images, without low contrast and blocking effects (Figures 9(h), 10(h), 11(h), 12(h), 13(h), and 14(h)). From the evaluation indicators in Tables 7–12, FFST-SR-PCNN had better performance than the other five comparing algorithms on QAB/F by an average increase of 31.7%. FFST-SR-PCNN is not always the best one in each individual evaluation indicators, but it never ranked less than top two. It can be seen that the computational efficiency of the proposed method was lower than comparing algorithm 5 (average 17.7% lower), while higher than the other four methods (average 40.35%, 76.8%, 69.8%, and 64.4% higher, respectively). This is because the number of iterations of the comparison algorithm 5 is relatively small, but its other indicators were not as good as the proposed algorithm.

Table 1: Quality assessment of CT/MR-T2 medical image fusion.

| Index   | Method 1 | Method 2 | Method 3 | Method 4 | Method 5 | FFST-SR-PCNN |
|---------|----------|----------|----------|----------|----------|--------------|
| SF      | 34.2861  | 34.3181  | 30.7780  | 30.6366  | 36.6748  | **36.9338**  |
| AG      | 9.6513   | 8.2010   | **10.0870** | 9.6272   | 9.2317   | 9.6804       |
| MI      | 2.1254   | 2.2705   | 2.0769   | 2.2199   | **2.9953** | 2.5248       |
| QAB/F   | 0.5190   | 0.4850   | 0.4939   | 0.5257   | 0.5843   | **0.5995**   |
| RT/s    | 16.2069  | 32.4554  | 30.5628  | 22.5256  | **8.7295** | 11.3624      |

Table 2: Quality assessment of CT/MR-T2 medical image fusion.

| Index   | Method 1 | Method 2 | Method 3 | Method 4 | Method 5 | FFST-SR-PCNN |
|---------|----------|----------|----------|----------|----------|--------------|
| SF      | 27.0626  | 26.9760  | 26.3291  | 23.9678  | 28.7623  | **29.3344**  |
| AG      | 9.6513   | 8.2010   | 10.0870  | 9.6272   | 9.2317   | 7.2640       |
| MI      | 2.1941   | 2.6101   | 2.2457   | 2.3168   | 2.9609   | **3.0805**   |
| QAB/F   | 0.4617   | 0.4088   | 0.5313   | 0.4733   | 0.5161   | **0.5473**   |
| RT/s    | 16.2266  | 32.3894  | 29.9843  | 22.0427  | **7.9451** | 10.1755      |
### Table 3: Quality assessment of CT/MR-T2 medical image fusion.

| Index | Method 1 | Method 2 | Method 3 | Method 4 | Method 5 | FFST-SR-PCNN |
|-------|----------|----------|----------|----------|----------|--------------|
| SF    | 37.5717  | 41.0988  | 36.5295  | 38.8050  | 40.0197  | **41.7215**  |
| AG    | 9.8877   | 8.9200   | 10.0862  | 10.2808  | 10.4221  | **10.4347**  |
| MI    | 2.0886   | 2.3744   | 2.0724   | 2.1990   | 2.4176   | **2.4719**   |
| QAB/F | 0.5559   | 0.5582   | 0.5242   | 0.6148   | 0.6300   | **0.6516**   |
| RT/s  | 16.2680  | 31.5377  | 30.1011  | 22.4004  | 8.3358   | 11.7004      |

### Table 4: Quality assessment of MR-T1/MR-T2 medical image fusion.

| Index | Method 1 | Method 2 | Method 3 | Method 4 | Method 5 | FFST-SR-PCNN |
|-------|----------|----------|----------|----------|----------|--------------|
| SF    | 22.7160  | 22.6900  | 21.5347  | 22.7164  | 24.3787  | **24.4962**  |
| AG    | 6.4857   | 6.3629   | 6.6983   | 6.4737   | 6.5910   | **6.8662**   |
| MI    | 2.3686   | 2.6473   | 2.4908   | 2.4517   | 2.9919   | 2.7319       |
| QAB/F | 0.5204   | 0.5614   | 0.6105   | 0.5686   | 0.6261   | **0.6416**   |
| RT/s  | 15.3972  | 27.2017  | 29.6786  | 22.8392  | 7.8440   | 8.5966       |

### Table 5: Quality assessment of MR-T1/MR-T2 medical image fusion.

| Index | Method 1 | Method 2 | Method 3 | Method 4 | Method 5 | FFST-SR-PCNN |
|-------|----------|----------|----------|----------|----------|--------------|
| SF    | 33.0368  | 35.8930  | 26.6605  | 30.3170  | 33.7416  | **34.2538**  |
| AG    | 12.8183  | 13.6667  | 10.2990  | 11.7227  | 12.8446  | **13.3015**  |
| MI    | 2.7059   | 4.0357   | 2.4716   | 2.6096   | 2.9629   | 3.2689       |
| QAB/F | 0.6086   | 0.6540   | 0.5126   | 0.5333   | 0.5285   | **0.6353**   |
| RT/s  | 16.2837  | 27.2017  | 29.6786  | 22.8392  | 7.8440   | 8.5966       |

### Table 6: Quality assessment of MR-T1/MR-T2 medical image fusion.

| Index | Method 1 | Method 2 | Method 3 | Method 4 | Method 5 | FFST-SR-PCNN |
|-------|----------|----------|----------|----------|----------|--------------|
| SF    | 25.6557  | 25.1765  | 23.7800  | 23.2217  | 26.4393  | **27.8123**  |
| AG    | 9.8287   | 9.3917   | 8.9306   | 8.9716   | 9.5509   | **10.2213**  |
| MI    | 2.5279   | 3.1267   | 3.1352   | 2.5935   | 3.7742   | 3.1781       |
| QAB/F | 0.4634   | 0.4707   | 0.5005   | 0.4656   | 0.5478   | **0.5724**   |
| RT/s  | 16.2837  | 34.0250  | 31.1384  | 22.7084  | 8.2634   | 12.1475      |

Figure 9: MR-T2/PET medical image fusion results. (a) MR-T2 original image. (b) PET original image. (c) Method 1. (d) Method 2. (e) Method 3. (f) Method 4. (g) Method 5. (h) FFST-SR-PCNN.
Overall, FFST-SR-PCNN had the best effect and can provide better fused medical images with relative lower computing cost.

Taken above gray images and color images fusion results together, FFST-SR-PCNN can achieve better fusion performance in edge sharpness, change intensity, and contrast.

Figure 10: MR-T2/PET medical image fusion results. (a) MR-T2 original image. (b) PET original image. (c) Method 1. (d) Method 2. (e) Method 3. (f) Method 4. (g) Method 5. (h) FFST-SR-PCNN.

Figure 11: MR-T2/PET medical image fusion results. (a) MR-T2 original image. (b) PET original image. (c) Method 1. (d) Method 2. (e) Method 3. (f) Method 4. (g) Method 5. (h) FFST-SR-PCNN.
To promote the fusion performance of unimodal medical images, this thesis proposed a FFST-SR-PCNN algorithm based on FFST, sparse presentation, and pulse-coupled neural network. It has excellent detail delineation and can efficiently extract the feature information of images, thus enhanced the overall performance of the fusion results. The

5. Conclusion

Figure 12: MR-T2/SPECT medical image fusion results. (a) MR-T2 original image. (b) SPECT original image. (c) Method 1. (d) Method 2. (e) Method 3. (f) Method 4. (g) Method 5. (h) FFST-SR-PCNN.

Figure 13: MR-T2/SPECT medical image fusion results. (a) MR-T2 original image. (b) SPECT original image. (c) Method 1. (d) Method 2. (e) Method 3. (f) Method 4. (g) Method 5. (h) FFST-SR-PCNN.
performance of FFST-SR-PCNN is evaluated by several experiments. In the comparing experiments with 5 comparison algorithms, all single-evaluation indexes of our algorithm are ranked in the top three; the comprehensive evaluation index of our algorithm has best result, and its QAB/F is higher than other 5 comparison algorithms. In
terms of subjective manner, FFST-SR-PCNN can efficiently express the marginal information of images and make the details of fusion image clearer, with more smooth edges. Thus, it has better subjective visual effects.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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