Multimodal Medical Image Fusion in Extended Contourlet Transform Domain

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Abstract. As a novel of multi-resolution analysis tool, the modified sharp frequency localized contourlet transforms (MSFLCT) provides flexible multiresolution, anisotropy, and directional expansion for medical images. In this paper, we proposed a new fusion rule for multimodal medical images based on MSFLCT. The multimodal medical images are decomposed by MSFLCT. For the high-pass subband, the weighted sum modified laplacian (WSML) method is used for choose the high frequency coefficients. For the lowpass subband, the maximum local energy (MLE) method is combined with "region" idea for low frequency coefficient selection. The final fusion image is obtained by applying inverse MSFLCT to fused lowpass and highpass subbands. Abundant experiments have been made on groups of multimodality datasets, both human visual and quantitative analysis show that the new strategy for attaining image fusion with satisfactory performance.

Keywords: multimodal medical image fusion, maximum local energy, contourlet transform.

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1 Introduction

The important of image processing and fusion has been investigated for diagnostic and healthcare [1]. Registration and fusion of radiological images is by no means a new post processing technique. Technological advances in medical imaging in the past three decades have enable radiologists to create images of the human body with unprecedented resolution.

The medical equipment companies like GE, Siemens, Hitachi et al. build the imaging devices (such as CT, PET and MRI scanners), which quickly acquire the body's 3D images. Such images provide different and often complementary contents, e.g. CT images supply anatomical information, PET images deliver functional information, and MR images are better in present the normal and pathological soft tissue. That is to say, imaging sensors provide a system with useful information regarding some features of interest in the system environment. However, a single sensor cannot provide a complete view of the scene in many applications. The fused images, if suitably obtained from a set of source sensor images, can provide a better view than that provided by any of the individual source images. In recent decades, growing interest has focused on the use of multiple sensors to increase the capabilities of intelligent machines and systems. As a result, multi-sensor fusion has become an area of intense research and development in the past few years.

The literature has published on data fusion in many fields, such as computer vision, machine intelligence and medical imaging, this paper is focused on multi-sensor data fusion in the multimodal medical images field.Multimodal medical image fusion is the process of extracting significant information from multiple images and synthesizing them in an image. In literature, it is well established that the multi-resolution analysis is the approach that best suits image fusion.

Some Multi-resolution Analysis (MRA) based fusion multimodal medical methods [2], such as wavelets [3], Laplacian pyramids [4], wedgelets [5], bandelets [6,24], curvelets [7,25], contourlets [8], have been recognized as one of the most methods to obtain a fine fusion images at different resolutions. As we fully and comprehensively elaborate the advantages and disadvantages of various X-lets transform in our previous work [9,23,26]. Here, we consider using a contourlet transform-based method for multimodal medical image fusion.

In this paper, we propose an image fusion method for multimodal medical images fusion, which operates in the modified sharp frequency localized contourlet transform (MSFLCT). We apply maximum local energy method (MLE) and weighted sum-modified Laplacian (WSML) in this work. Particularly, for multimodal images fusion, we selected the low frequency coefficients by the proposed maximum local energy (MLE) method, and introduced weighted sum modified Laplacian (WSML) to calculate the high frequency coefficients. The structure of the following is: In Section 2, we briefly introduce the modified sharp frequency localization contourlet transform in this work. As a solution, we propose in Section 3 a new fusion method, named maximum local energy method and weighted sum modified Laplacian method. Numerical experiments are presented in Section 4 to confirm our method. Finally, we conclude the paper in Section 5.

2 Modefied Sharp Frequency Localized Contourlet Transform

Do and Vetterli [8] proposed an efficient directional multi-resolution image representation called contourlet transform in 2002. Contourlet is a “true” two-dimensional transform that can capture the intrinsic geometrical structure, and has been applied to several tasks in image processing. Contourlet transform (CT) better represents the salient features of the image such as edges, lines, curves, and contours, than wavelet transform because of its anisotropy and directionality. Two steps are involved in CT, which are subband decomposition and the directional transform. CT uses the Laplacian pyramid (LP) transform to decompose the image in multiscale form before adopting the directional filter banks (DFB) to decompose the high frequency coefficients and obtain details with different directions of the directional subband. CT can accurately express directions. However, because of the non-subsampled process in LP and DFB, it causes frequency aliasing, which creates larger changes in decomposition coefficient distribution with a small shift in the input image. However, if we fuse the decomposition coefficients, the process results in edge aliasing or the pseudo-Gibbs phenomena. Therefore, non-subsampled contourlet transform (NSCT) was created simply by turning the downsampler units in the subsampled contourlet by considering some aliasing issues. But the NSCT has the weakness of high redundancy and long run time. As a solution, Y. Lu proposed a new construction of a sharp frequency localization contourlet transform (SFLCT) [10].

Sharp Frequency Localized Contourlet Transform (SFLCT) is a new construction contourlet which succeed in solving the pseudo-Gibbs phenomena around singularities procuced by the Laplacian pyramid stage. The difference between SFLCT and Contourlet transform (CT) is that, SFLCT use the new multiscale pyramid and can employ a different set of lowpass and highpass filters for the levels. Suppose lowpass filters $L_i(\omega)$ (i = 0,1) in the frequency domain as $L_i(\omega) = L_i^{ld}(\omega_1)\cdot L_i^{ld}(\omega_2)$, and $L_i^{ld}(\omega)$ is a one-dimensional lowpass filter with passband frequency $\omega_{p,i}$ and stopband frequency $\omega_{s,i}$ and a smooth transition band, defined as

$$L_i^{ld}(\omega)=\begin{cases} 1 & for|\omega|\leq\omega_{p,i,} \\ \frac{1}{2}+\frac{1}{2}\cos\frac{(|\omega|-\omega_{p,i})\pi}{\omega_{s,i}-\omega_{p,i}} & for\omega_{p,i}<|\omega|<\omega_{s,i} \\ 0 & for\omega_{s,i}\leq|\omega|\leq\pi \end{cases} \tag{1}$$

where $|\omega|\leq\pi$ and i =0,or 1. The Figure 1 shows the new pyramid structure of SFLCT, instead of using the Laplacian pyramid.

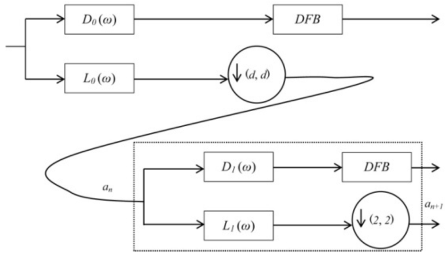

Fig. 1 The block diagram of Sharp Frequency Localized Contourlet Transform

SFLCT succeeded solve the pseudo-Gibbs phenomena, but it was not solved the shift variant, due to the downsampling of Laplacian pyramid and DFB stages. Hence, we use cycle spinning [11] for shift invariant denoising.

Suppose f_1, f_2 are source images and F is the fused image, C_{-1},C are the inverse MSFLCT and forward MSFLCT, $S_{x,y}$ is the cycle spinning method and x,y are the shift arranges in horizontal and vertical directions. Cycle spinning fusion rule is

$$F=S_{-x,-y}\{h[C(\,S_{x,y}(f_1)\,),\,C(\,S_{x,y}(f_2)\,)]\} \tag{2}$$

where, h is the function process in SFLCT domain. $x\in X$ and $y\in Y$ is the shift arranges, $X=\{x_1,x_2,\ldots,x_m\}$, $Y=\{y_1,y_2,\ldots,y_n\}$. Therefore, cycle spinning averages the dependence of directional filter banks of SFLCT. It can be defined as

$$F = Ave_{x\in X,y\in Y}\left\{S_{-x,-y}\left\{h\left[C\left(S_{x\in X,y\in Y}(f_1)\right),C\left(S_{x\in X,y\in Y}(f_2)\right)\right]\right\}\right\} \tag{3}$$

3 The Proposed Fusion Algorithm

In this section, we propose a new multimodal medical image fusion method. Figure 2 shows the flowchart of a MSFLCT-based scheme suitable for fuse the multimodal medical images, whose scale is an integer p=3. Let $f^{(P)}(i,j)$ be the dataset constituted by modal 2 image with smaller scale, and size is $M_P\times N_P$. Let also $f^{(l)}(i,j)$ be the dataset made up of an Modal 1 image. The enhancement of each band to yield the spatial resolution of Modal 1 image is synthesized from the layer c_1 (middle layer) and c_2 (high layer) of the MSFLCT.

Firstly, obtain $f^{(l)}(i,j)$ of Modal 1 with the same spatial resolution as Modal 2 image. The constitution of low-resolution component of Modal 2 image and Modal 1 image are processed by maximum local energy (MLE) rule. In the level i_1 of resolved Modal 2 image and Modal 1 image, the local energy components are obtained by 3×3 sliding window. Then, output the maximum component of two source images. In the layer c_1 (middle layer) and c_2 (high layer), we use a spatial domain measurement, the weighted sum modified Laplacian (WSML), as a high-resolution fusion rule. The modified Laplacian takes the absolute values of the second derivatives in the Laplacian to avoid the cancellation of the second derivatives in the horizontal and vertical directions that have opposite signs. At the same time, MLE rule can adaptive to adjust WSML rule. Finally, by means of the inverse MSFLCT, two images of zero-mean spatial edges and textures that are added to the corresponding frames. The final medical fused image $f^{(l)}(i,j)$ is received by summing the approximations and enhanced detail frames of each band in MSFLCT synthesis.

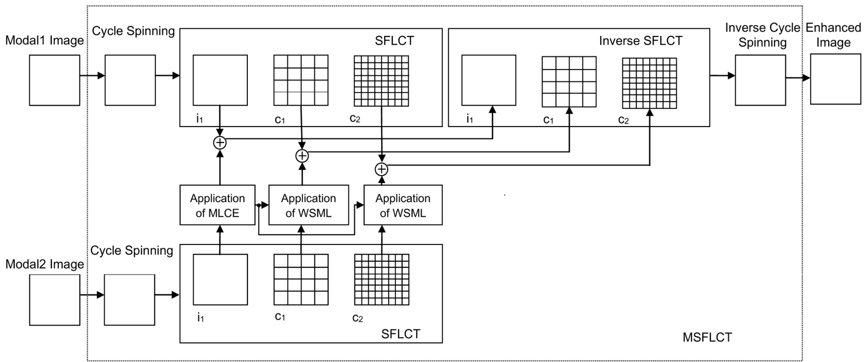

Fig. 2 The flowchart of our fusion rules

3.1 Lowpass Subband Fusion Rule

This paper proposes the maximum local energy (MLE) as a measurement for low frequency selection. Due to the incompleteness of multiscale decomposition, image details are mainly retained in the low frequency. Therefore, proposed some edge filters to get a good result. But because of the edge filter coefficients distribute as non-Gaussian distribution, so, combine with local energy, can solve this problem well. Select the maximum energy of two low layer i_1 images as output. Due to the partial human visual perception characteristics and the relationship of decomposition about local correlation coefficients, the statistical characteristics of neighbor should be considered. Therefore, the statistic algorithm is based on the 3×3 sliding window. The algorithm is described as follows:

$$\mathrm{LE}_{\xi}(i,j)=\sum_{i'\in M,j'\in N} p(i+i',j+j')\bullet f_{\xi}^{(0)2}(i+i',j+j') \tag{4}$$

where p is the local filtering operator. M, N is the scope of local window. $\xi \in A$ or B (A, B is the window for scanning two images). $f_{\xi}^{(0)}(i,j)$ is low frequency coefficients, and i, j are variables. So, the Maximum Local Contourlet Energy (MLCE) are defined as

$$\begin{aligned} Max\ LCE_{\xi}^{l,k}(i,j) &= E_1 * f_{\xi}^{(0)2}(i,j) + E_2 * f_{\xi}^{(0)2}(i,j) \\ &+ \cdots + E_K * f_{\xi}^{(0)2}(i,j). \end{aligned} \tag{5}$$

where $E_1,E_2,\ldots, E_{K-1}$ and E_K are the filter operators in K different directions. l is the scale layer.

$$E_1 = \begin{bmatrix} -1 & -1 & -1 \\ 2 & 2 & 2 \\ -1 & -1 & -1 \end{bmatrix}, E_2 = \begin{bmatrix} -1 & 2 & -1 \\ -1 & 2 & -1 \\ -1 & 2 & -1 \end{bmatrix}, E_3 = \begin{bmatrix} -1 & 0 & -1 \\ 0 & 4 & 0 \\ -1 & 0 & -1 \end{bmatrix} \tag{6}$$

The principle of the MLE method can be elaborated by Figure 3. In the scale J matrix in MSFLCT domain, use (4) to convert the coefficients values to energy values. A sliding window, with 3 directions, is moving through the energy matrix, and output the maximum coefficient as the fuse coefficients.

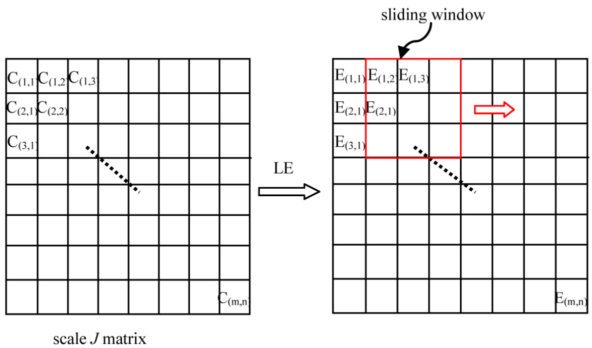

Fig. 3 The principle of Maximum Local Energy rule

Suppose $I_A^{l,k}(i,j)$, $I_B^{l,k}(i,j)$ and $I_F^{l,k}(i,j)$ denote the coefficients of source images and fused images. The proposed MLCE-based low frequency coefficients fusion rule can be described as follows

$$I_F^{l,k}(i,j) = \begin{cases} I_A^{l,k}(i,j), if: MLCE_A^{l,k}(i,j) \geq MLCE_B^{l,k}(i,j) \\ I_B^{l,k}(i,j), if: MLCE_A^{l,k}(i,j) < MLCE_B^{l,k}(i,j) \end{cases} \tag{7}$$

3.2 Highpass Subband Fusion Rule

Assuming that the image details are contained in the high-frequency subbands in the multiscale domain, the typical fusion rule is a maximum-based rule, which selects high-frequency coefficients with the maximum absolute value. Recently, measurements such as, energy of gradient (EOG) [12], spatial frequency (SF)[13], Tenengrad[14], energy of Laplace (EOL)[15], and sum modified Laplacian (SML) [16] have been used. In this paper, In Ref. [17], the authors declaimed that SML has a better performance than the others. However in this paper, we propose a new type of SML, called Weighted SML (WSML). We use WSML to choose the high frequency coefficients in MSFLCT domain. The WSML is more reasonable to employ the features of coefficients, which considering the relationship between the neighbor coefficients.

A focus measure is defined in a maximum for the multimodal medical images. Therefore, for multimodal image fusion, the focused image areas of the source images must produce maximum focus measures. Set $f(x,y)$ as the gray level intensity of pixel (x,y). Defined modified Laplacian (ML) is

$$\begin{aligned}\nabla^2_{ML} f(x,y) = & |2f(x,y) - f(x-step,y) - f(x+step,y)| \\ & + |2f(x,y) - f(x,y-step) - f(x,y+step)|.\end{aligned} \tag{8}$$

In this paper, "step" is always equals to 1. We use a city-block distance matrix to modify the traditional SML formulation as

$$WSML_x^{l,k}(i,j) = \sum_{i=-M}^{M} \sum_{j=-N}^{N} W \nabla^2_{ML} f(i+p, j+q), \nabla^2_{ML} f(i,j) \geq T \tag{9}$$

where l and k are the scale and the direction of transform respectively. $x \in A$ or B are the source images. T is a discrimination threshold value. M and N determine the window with a size of $(2M + 1) \times (2N + 1)$, and p, q are variables. The city-block distance matrix is

$$W = \frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \tag{10}$$

Suppose $C_A^{l,k}(i,j)$, $C_B^{l,k}(i,j)$, and $C_F^{l,k}(i,j)$ denote the coefficients of the source and fused images. The proposed WSML-based high frequency coefficients fusion rule can be described as follows:

$$C_F^{l,k}(i,j) = \begin{cases} C_A^{l,k}(i,j), if: WSML_A^{l,k}(i,j) \geq WSML_B^{l,k}(i,j) \\ C_B^{l,k}(i,j), if: WSML_A^{l,k}(i,j) < WSML_B^{l,k}(i,j) \end{cases}. \tag{11}$$

4 Experimental Results and Discussions

To evaluate the performance of the proposed approach, we present with dataset is CT and MR images. The images are registered images, which are with the same size of 256×256 pixel and with 256-level grayscale. The average pixel value method provides a baseline result, while the PCA fusion method givers an equivalent but a slightly better result. However, both of the methods have poor results compared to the others by human vision. Because of both of them do not consider the scale selectivity. Through the results in multiscale methods, which present in Figure 4, we found that the details of Figure 4(e), (f) and (g) are blurred. This is very bad for doctor's diagnosis.

Back to review the reason of the blurring in the principle level. We found that although the themes of classical wavelets are compression and efficient in signal representation. The important features in the analysis of functions in two variables are dilation, translation, spatial and frequency localization, and singularity orientation. For one dimension, important singularities are simply points. But the one-dimensional singularities are important in two-dimensional signal or higher. Smooth singularities in two-dimensional images often occur as boundaries of physical objects. Efficient representation in two dimensions is a hard problem in wavelet representation. That's why the wavelet transform limited in medical image fusion. Using curvelet transform, blocks must be overlapped together to avoid the boundary effect. Therefore, redundancy is higher in this implementation algorithm. The other reason is that the key step in curvelet transform, Cartesian to polar conversion, cause mistakes in the fused results. In section 2, we elaborated the drawbacks of traditional contourlet transform. Generally speaking, the proposed method achieves the best overall performance. We also test the proposed method in 100 clinic medical sample images, the PSNR value of the results are also shows that the proposed method is well in processing the multimodal medical images.

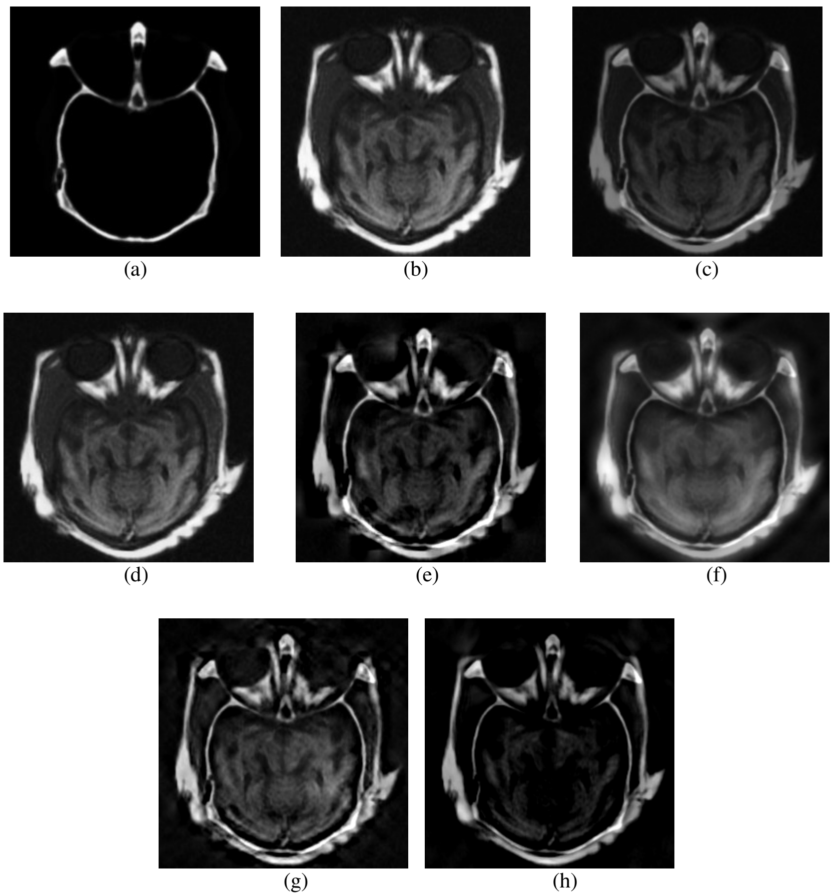

Fig. 4 Test CT/MR images fused results with different method. (a) CT image. (b) MR image. (c) Average method. (d) PCA. (e) Wavelet. (f) Curvelet. (g) Contourlet. (h) Proposed method.

In addition to the visual analysis of these figures, we conducted quantitative analysis, mainly from the perspective of mathematical statistics and the statistical parameters of the images. These include entropy (EN), [18] average gradient (AG)[19] Peak Signal to Noise Ratio (PSNR) [20], fusion quality index (Q) [21], Structural SIMilarity (SSIM) [22].

Entropy of image reflects the amount of its carried information. The more information it carried, the larger its value. The computational formula is given by

$$H = -\sum_{l=0}^{L-1} p_F(l) \ln p_F(l) \tag{12}$$

where, $l \in \{0,1,2,\ldots,L-1\}$, $p_F(l)$ is the probability of fused image F at gray-level l.

The average gradient reflects the small details of the image, texture variation and clarity. If this value is larger, the fused image better. It is defined by

$$g = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} \left[(\Delta F_x^{\ 2} + \Delta F_y^2) / 2 \right]^{1/2} \tag{13}$$

where, $\Delta F_x = F(x, y+1) - F(x, y), \Delta F_y = F(x+1, y) - F(x, y)$.

Let x_i and y_i be the i-th pixel in the original image $\mathbf{x}$ and the distorted image $\mathbf{y}$, respectively. The MSE and $PSNR$ between the two images are given by

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (x_i - y_i)^2, \tag{14}$$

$$PSNR = 10 \log_{10} \left(\frac{L^2}{MSE} \right) \tag{15}$$

In [22], the authors use a sliding window, from the top-left of the two images A, B. The sliding window is with a fixed size. For each window w, the local quality index $Q_0(A, B| w)$ is computed for the values $A(i, j)$ and $B(i, j)$, where pixels (i, j) lies in the sliding window w.

$$Q_0(A, B) = \frac{1}{|W|} \sum_{w \in W} Q_0(A, B \mid w), \tag{16}$$

where W is the family of all windows and $|W|$ is the cardinality of W. In practice, the Q_0 index also defined as

$$Q_0(A, B) = \frac{\sigma_{AB}}{\sigma_A \cdot \sigma_B} \cdot \frac{2\overline{A} \cdot \overline{B}}{\left[(\overline{A})^2 + (\overline{B})^2 \right]} \cdot \frac{2\sigma_A \cdot \sigma_B}{(\sigma_A^2 + \sigma_B^2)} \tag{17}$$

where, σ_{AB} denotes the covariance between A and B, $\overline{A}$ and $\overline{B}$ are the means, $\sigma^2{}_A$ and $\sigma^2{}_B$ are the variances of A and B, respectively.

Piella et al. [21] redefined the useful quality index Q_0 as $Q(A, B, F)$ for image fusion assessment. Here A, B are two input images and F is the fused image. They denoted by $s(A|w)$ some saliency of image A in window w. This index may depend on contrast, sharpness, or entropy. The local weight $\lambda(w)$ is defined as

$$\lambda(w) = \frac{s(A \mid w)}{s(A \mid w) + s(B \mid w)} \tag{18}$$

where $s(A|w)$ and $s(B|w)$ are the local saliencies of input images A and B, $\lambda \in [0,1]$. The fusion quality index Q $(A,B.F)$ as

$$Q(A,B,F) = \frac{1}{|W|} \sum_{w \in W} \left(\lambda(w) Q_0(A,F \mid w) + (1-\lambda(w)) Q_0(B,F \mid w) \right) \tag{19}$$

In [22], a multi-scale SSIM method for image quality assessment is proposed. Input to signal A and B, let μ_A, σ_A and σ_{AB} respectively as the mean of A, the variance of A, the covariance of A and B. The parameters of relative importance α, β, γ are equal to 1. The SSIM is given as follow:

$$SSIM(\mathrm{x},\mathrm{y}) = \frac{(2\mu_A \mu_B + C_1)(2\sigma_{AB} + C_2)}{(\mu_A^2 + \mu_B^2 + C_1)(\mu_A^2 + \mu_B^2 + C_2)} \tag{20}$$

where C_1, C_2 are small constants. From the Table 1, the proposed method is better than the other multi-resolution analysis methods in multimodal medical images fusion. From the below three image sets, the value of Q and SSIM is higher than the others, which is the higher the better.

Table 1 Conparation of different multimodal medical image fusion methods

Algorithms	EN	AG	PSNR	Q	SSIM
Average	5.9152	3.6606	15.657	0.6613	0.74338
PCA	6.5814	5.0795	17.691	**0.8521**	0.85590
Wavelet	5.9727	6.4312	17.126	0.5262	0.58745
Curvelet	**7.1056**	4.3369	20.269	0.5913	0.82041
Contourlet	6.6061	**6.9663**	18.261	0.5825	0.72138
Proposed	4.0455	4.8149	**24.011**	0.6073	**0.90545**

5 Conclusions

In this paper, we proposed a new multimodal medical image fusion method, based on modified sharp frequency localized contourlet transform (MSFLCT). The novel approach is applied on larger number of dataset of category and simulation results are found with superior visual quality compared to other stand-of-art image fusion methods. We respectively applied two different rules in lowpass subband and highpass subband. The proposed algorithm can be extended further by applying it for different categories of images like remote sensing images. Visual and statistical comparisons demonstrate that the fusion results of the new algorithm contain more detail information than others. In future, complex fusion rules and their combinations can be explored to improve robustness of proposed multimodal medical image fusion approach.

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