Multimodal medical image fusion using laplacian redecomposition

K KoteswaraRao1 and K Veera Swamy2

ECE Department, JNTUK, Kakinada, Andhra Pradesh, India, E-mail: koti_r@yahoo.in
ECE Department, Vasavi College of Engineering, Hyderabad, India, E-mail: k.veeraswamy@staff.vce.ac.in

Abstract: Fusion of multi-modality images gives more sophisticated and complete information in video surveillance, remote sensing, and medical diagnosis. The present paper delivers a contemporary fusion method using laplacian redecomposition. The area of medical image fusion with different modalities has achieved more progress in medical field. Existing methods suffer from noise, blurring, and color distortion. These complications are addressed in the present method. The authors propose laplacian redecomposition method after enhancement to get redundant and complementary information. The proposed method has two alterations. First, we give the concept of overlap and non-overlap domains. Overlap and non-overlap domains are used for fusing redundant and complementary information respectively. Second, decision graph scheme is presented to get low frequency sub band images, complementary and redundant information. Global decision graph is used for reconstructing HF sub band images. Lastly, by taking inverse laplacian operation fused image is obtained. In the experiments for comparison, a few pairs of medical images have been taken to prove the strength of the suggested technique. The experimental results demonstrate that, the proposed technique accomplish aggressive performance qualitatively and quantitatively.

Keywords: Image fusion, laplacian redecomposition, medical modalities, overlap, non-overlapping domains

1. INTRODUCTION

As a fundamental and capable appliance, medical images play incorrugible role in the medical treatment and diagnosis. Fusion of medical images is the process of merging information of various source images of the same object. It is an effective process to improve human perception [1]. Medical image fusion of different modalities is one of the subfields of image fusion and it has outstanding advancement for several years [2]. Especially, anatomic image fusion is considered as good research area [3]. There are number of medical image modalities, which include computed tomography, magnetic resonance imaging, positron emission tomography, and single photon emission computed tomography to consign various lesions. Each modality has its own features and weaknesses. CT is good at information about bone structure and is poor to give the information of soft tissues and metabolism. MRI is good at information of soft tissues and is poor at the information of bone structure. PET is good at information of organ blood flow but poor in giving the information about bone structure. SPECT gives the information of metabolism. But PET and SPECT have low resolution. To take accurate decision by the doctors, complete and reasonable information is needed. [4] Image fusion of medical images achieves this role by fusing two or more images from different modalities. In this way better information from all modalities is gained. There are three levels by which fusion is performed. These levels are pixel, feature, and decision levels. Fusion at
pixel level is performed by taking small unit. In this, co-registration of two images is done. At the feature level, matching of features of one image is done with features of another image. At the decision level, both the images are analyzed and collected separately to obtain improved image.

Fusion methods are divided into spatial and transform methods [5], [6]. In spatial method, the image pixels are taken to get the fused image. In this domain, every information from the pixels is preserved perfectly. The features present in the fused image must be matched with the information of input images with multi-focus [7], [8]. But the shortcomings of this domain are reduction in sharpness and contrast which are not acceptable. Transform based techniques are generally preferred for fusing medical images [9], [10]. This domain transforms the input images into coefficients. The coefficients of these images are merged by suitable fusion strategy and by making inverse operation, reconstructed output image is obtained. MST and SR are the popular methods for fusing medical images. MST based methods are frequency domain methods in which LF and HF sub bands are decomposed from source images. These bands are fused by suitable fusion algorithm to get fused output. Sparse representation is the time domain method. In this representation, sparse coefficients are obtained from source images using dictionary learning. Liu [11] suggested an adaptive sparse representation method for all types of medical image fusion. Kim [12] implemented an eminent method of dictionary learning using sparse representation for image fusion. This method decreases the computational cost. Li [13] suggested a LR and DL technique for noisy images. The input images are coded sparsely using fusion rule. The fused output contains more meaningful information. But this method takes more time compared to other methods.

MST is the more powerful algorithm among transform domain methods. The methods based on MST, like DWT [14], CT [15], ST [16], NSCT [17], [18], and NSST [19], [20] are regularly used. NSST and NSCT based fusion methods are proved to be efficient methods. LIU [21] suggested a common framework for IR medical fusion. This work, based on NSCT was proved to be an efficient method. Du [22] suggested a method to fuse functional and anatomical images. Local laplacian filter is used as tool for structural data and enhances clear information. At the same time, local energy maximum scheme generates residual image and approximate image. The image after fusion is achieved by the process of reconstruction which is same as laplacian pyramid transform. Another framework using NSCT was proposed [23]. In this work, SR has been applied to integrate LF co-efficients. But, HF sub band fusion rule based on local energy could not effectively solve smoothness of image details due to SR. NSCT [24] using variable weight rule solved this fusion issue. Decomposition of LF and HF sub bands is done by NSCT [25]. The LF components have been fused using a metric related to Shannon entropy and HF components have been fused using directive contrast. By using this method functional information and spatial features are preserved. Gansala and Kumar [26] have proposed a scheme based on NSCT where LF co-efficients are fused by local window co-efficients and HF co-efficients are fused by modified laplacian. Li [27] proposed the framework based on SR and NSCT to preserve and enhance meaningful details. In this work, LF sub bands are fused by SR and HF sub bands are fused by SML. Considering the above discussions, it is observed that decomposition algorithm and fusion rules are the main factors to get better fused output. Traditional laplacian scheme could not explain structural information [28]. Du [29] performed laplacian filtering using laplacian decomposition algorithm. In laplacian filtering, edge preserving filters have been used to sharpen the images. The problems observed with this method are 1. Edge preserving filter failed to eliminate noise. 2. Laplacian filter could not desparate the redundant and complementary data among different sub images. 3. Few wrong decisions are made. Koteswara Rao et al [31], [32] proposed dual level fusion using NSCT, DWT and spatial domain. In this the results are good at second level. To address above problems, authors suggest new algorithm based on laplacian redecomposition (LRD). In this lifting co-efficients and mapping functions are used to highlight image details. While fusing HSI, complementary and redundant information cause errors. So, we propose an
idea to categorize complementary and redundant information. In this way, we obtain overlapping and non-overlapping images. While fusing OD images, authors use decision scheme considering intensity and energy. But, the non-overlapping has no significance on redundant information. So, authors develop simple rule that eliminates distortion. The reconstruction of HSI causes artifacts which are due to desperate fusion of complementary and redundant information. Therefore, IRS fusion rule is used. The major work of this method are outlined as:

1. Authors present LRD scheme and it decomposes LSI and HSI simultaneously.
2. OD and NOD are presented for constructing fusion rules.
3. ILRD rule is introduced to reconstruct HF images using decision graphs.
4. LRD preserves more useful information and is more effective qualitatively as well as quantitatively.

The organization of the proposed paper is as follows. Section II proposes preliminaries of LRD, section III covers proposed method, experimental results are given in IV section, and lastly conclusions are given in the concluding part.

2. PRILIMANARIES

In this section, the preliminaries of laplacian redecomposition are given. Figure1 shows the schematic diagram of LRD. It has GDIE [30], DGR, and LP. GDIE is responsible for enhancement of LRD’s capability. LP decomposes the image in multiple scale fashion. DGR establishes the global decision graphs to provide OD and NOD images to get fusion result.

2.1 GDIE: GDIE consists of four components. MLD, division of feature information, convolution operation, and remapping features.

2.1.1 MLD: In this, every 3 pixel point is divided as 12 directions. After that, summation of pixels in every direction is forecasted and then maximum difference is expressed as

\[ D(j, k) = \sum_{j=1}^{m} \sum_{k=1}^{n} \left[ \max \sum_{x=1}^{12} z(x) - \min \sum_{x=1}^{12} z(x) \right] \]  

(1)

Where D (j, k) represents the value of MLD and Z(x) is the sum of all pixel in every direction.

2.1.2 IDFI: The threshold value is selected to divide edge information. This threshold has two steps.

I. Arrange D (j, k) from higher to lower to make 1-D array.

II. Rate of array Y is calculated with fixed length when its value is below 0.1, MLD is taken as threshold

\[ R_{j} = \sum_{j=1}^{\lceil j+k \rceil} V_{j} - V_{j+k} \]  

(2)

\[ T = V_{j}, \text{if } R_{j} < 0.1 \]  

(3)

Where k= (m x n)/l, l represents fixed length, V is the size of array, m x n is the total length.

2.1.3 Adaptive HF Information Lifting Co efficient: Adaptive HF information lifting coefficient C (j, k) depends on both MLD and fitting function Y1. Considering fitting co-ordinates, Y1 is calculated as
\[ Y_1(x) = \alpha_1 x^3 + \alpha_2 x^2 + \alpha_3 x + \alpha_4 \]  \hspace{1cm} (4)

\( \alpha_1, \alpha_2 \) are the coefficients.

Considering equation 1 and \( Y_1 \), \( C(j, k) \) is calculated as

\[
C(j, k) = \begin{cases} 
(D(j, K)) & D(j, K) > 0 \\
-1 & D(j, K) = 0
\end{cases}
\]

\hspace{1cm} (5)

### 2.1.4 Gradient Re mapping Image Enhancement:

The localized information of gradient of the image is expressed as

\[
g_1(x) = \sum_{\theta=-1}^{1} \sum_{\delta=-1}^{1} [p(j + \theta, k + \delta) - p(j, k)]
\]

Where \( p(j, k), \theta \) and \( \delta \) represent pixels of source image, rows and columns of \( g_1 \) respectively.

Remapping of \( g_1 \) with \( C(j, k) \) and \( Y_2 \) give local template \( g_2 \). The ranges of \( g_1 \) and \( Y_2 \) are in between -1 and 1. The mapping function is 1 for better enhancement. The following relation represents these details.

\[
y_2(x_{\theta, \delta}) = w_2 x_{\theta, \delta} + w_2 + 1
\]

\hspace{1cm} (7)

\[
x_{(\theta, \delta)} = C(j, k) - \frac{C(j, k) + 1(\max(g_1) - \sum_{\theta=1}^{1} \sum_{\delta=1}^{1} g_1(\theta, \delta))}{\max(g_1) - \min(g_1)}
\]

\hspace{1cm} (8)

Higher the value of \( w_2 \) more is the enhancement.

\( X(\theta, \delta) \) is the variable and \( g_2 \) is obtained using equations 7 & 8

\[
g_2 = \sum_{\theta=1}^{3} \sum_{\delta=1}^{3} Y_2(x_{(\theta, \delta)})
\]

\hspace{1cm} (9)

The enhanced image is obtained by convoluting \( g_2 \) with source image

\[
H(j, k) = \sum_{j=1}^{m} \sum_{k=1}^{n} g_2 \odot A(j, k)
\]

\hspace{1cm} (10)

### 2.2 LP Multi Scale Decomposition:

LSI and HSI decomposition is done by laplacian pyramid. LP decomposition algorithm is

\[
H_{\mu}(j, k) = \sum_{\tau=1}^{r} I_{\mu}^{\tau}(j, k) + G_{\mu}^{\tau}(j, k)
\]

\hspace{1cm} (11)

Where \( I_{\mu}^{\tau} \) represents HSI and \( G_{\mu}^{\tau}(j, k) \) represents LSI, \( \mu \) is the source image, \( \tau \) represents total length and \( \gamma \) is the present length.

### 2.3 DGR Algorithm:

DGR separates the complementary and redundant information from HSI. DGR decomposes HSI into over-lapping and non-overlapping images. DGR utilizes global decision graphs of HSI. The redundant information is separated into overlapping images by first classifier \( m_s \).
Complementary information is stored into non-overlapping images by second classifier $m_6$ which is shown in the following algorithm.

Input: $I^y_{\mu}$, ($y = 1, 2$) , Outputs: $O^y_{\mu}, N^y_{\mu}$

1. $m_1 = \begin{cases} 1 & \text{if } \sum_{j=1}^{m} \sum_{k=1}^{n} I^y_A > 0 \\ 0 & \text{elsewhere} \end{cases}$

2. $m_2 = \begin{cases} 1 & \text{if } \sum_{j=1}^{m} \sum_{k=1}^{n} I^y_B > 0 \\ 0 & \text{elsewhere} \end{cases}$

3. $m_3 = m_1 + m_2$

4. $a = m_3$

5. $a = 0$ if $\sum_{j=1}^{m} \sum_{k=1}^{n} m_3 < 2$

6. $m_4 = \lambda \times \sum_{j=1}^{m} \sum_{k=1}^{n} a$

7. $m_5 = \begin{cases} 1 & \text{if } \sum_{j=1}^{m} \sum_{k=1}^{n} m_4 > 0 \\ 0 & \text{elsewhere} \end{cases}$

8. $m_3 = 0$, if $\sum_{j=1}^{m} \sum_{k=1}^{n} m_3 \geq 2$

9. $m_6 = m_3$

10. $O^y_{\mu}(j, k) = m_5 \times I^y_{\mu}(j, k)$

11. $N^y_{\mu}(j, k) = m_6 \times I^y_{\mu}(j, k)$

12. Return $O^y_{\mu}, N^y_{\mu}$

3. PROPOSED ALGORITHM

The schematic details of present work is presented in figure1. LRD decomposes the source images into LSI, overlapping and non-overlapping images of HSI. LSI gives approximate information and HSI gives detail information. Most of the information is present in the LSI. Edge and boundary information is present in the HF sub bands. To fuse LSI images, LEM fusion rule is used. To fuse overlapping and non-overlapping images, OD and NOD rules for fusion are used. After OD and NOD fusion there may be chance of existing artefacts at the output which are not present at the source images. To reconstruct HSI fusion image, IRS fusion rule is proposed. At this stage artefacts are eliminated. Finally, fused image is obtained by taking inverse laplacian operation.
3.1 LEM fusion: The information of interest of anatomical image is detail and texture. In LEM, square of the summation of the pixels is done. But, this square operation leads to instability. So, authors perform addition operation.

\[ Q_\mu(j, k) = \beta \sum_{x=-1}^{1} \sum_{y=-1}^{1} G^*_\mu(j + x, k + y) \]  

(12)

Where \( \beta \) is the filtering template and \( x, y \) represent sizes of the local window. The maximum value of \( Q_\mu \) as \( E_\mu \) are defined as LEM

\[ E_\mu(j, k) = \max \left( \sum_{x=-1}^{3} \sum_{y=-1}^{3} Q_\mu(j + x, k + y) \right) \]  

(13)

The fusion image \( G^3_F \) is obtained to construct the decision graph as

\[ m_7 = \begin{cases} 1, & E_A(j, k) > E_B(j, k) \\ 0, & \text{elsewhere} \end{cases} \]  

(14)

\[ G^3_F(j, k) = m_7 \times G^*_A(j, k) + \sim m_7 \times G^*_B(j, k) \]  

(15)

Where \( \sim \) is the inverse operator
3.2 OD Fusion: To fuse OD images which contains more meaningful information, there are three steps as follows:

1). Local decision maximum has been proposed to mark edges and important details.

2). By using LEM and MLD, another LDM method has been proposed for abnormal areas of functional images.

3). Binary decision graph is constructed by comparing the sizes LDM’s and fused image of overlapping domain is produced.

LDM is produced by using LEM and MLD as

\[ M_A(j, k) = D_A(j, k) + E_A(j, k) \]  \hspace{1cm} (16)

\[ M_B(j, k) = D_B(j, k) + \sim m_8 \times E_B(j, k) \]  \hspace{1cm} (17)

\[ m_8 = \begin{cases} 
1 & \text{if } M_A(j, k) > M_B(j, k) \\
0 & \text{elsewhere} 
\end{cases} \]

MB is the LDM value, m_8 is the decision graph

The fusion rule is obtained as

\[ O^V_F(j, k) = m_9 \times O^V_A(j, k) + \sim m_9 \times D^V_B(j, k) \]  \hspace{1cm} (19)

\[ O^V_F(j, k) \] is the OD fused image

3.3 NOD Fusion: Non overlapping image fusion is obtained by the following expression

\[ N^V_F(j, k) = N^V_A(j, k) + N^V_B(j, k) \]

Where N_A and N_B represent non overlapping domain images of functional. N_F represents fused output.

3.4 Inverse Re decomposition scheme: HF images are reconstructed by using IRS. Since redundant and complementary information images are fused desperately, it may cause unwanted information while doing reconstruction of HF images. To avoid these problems, two global decision graphs are constructed. This rule is outlined in the following algorithm

Input: \( O^V_F, N^V_F \)  
Output: \( L^V_F \)

1). \[ m_{10} = \begin{cases} 
1 & \text{if } O^V_F(j, k) > 0 \\
0 & \text{elsewhere} 
\end{cases} \]
2. \[ m_{11} = \begin{cases} 1 & \text{if } N_{P}^r (j,k) > 0 \\ 0 & \text{elsewhere} \end{cases} \]

3. \[ m_{12} = m_{10} + m_{11} \]

4. \[ m_{13} = \begin{cases} 1 & \text{if } 0 < m_{12} < 2 \\ 0 & \text{elsewhere} \end{cases} \]

5. \[ m_{14} = \begin{cases} 1 & \text{if } m_{12} > 1 \\ 0 & \text{elsewhere} \end{cases} \]

6. \[ L^r_P (j,k) = m_{13} \times O^r_P (j,k) + m_{13} \times N^r_P (j,k) + 0.5 \times (m_{14} \times O^r_P (j,k) + m_{14} \times N^r_P (j,k)) \]

7. Return \( L^r_P \)

### 3.5 Reconstructed fusion image

Fused image is reconstructed by taking inverse laplacian transform. The fused image is calculated as

\[ F(j,k) = \sum_{\tau=1}^{r-1} L^\tau_P (j,k) + G^r_P (j,k) \] (21)

### 4. EXPERIMENTAL RESULTS

#### 4.1 Experimental Setup

In this paper, four pairs of data sets from different modalities of sizes 256×256 which has been used as testing datasets. Out of four pairs, two pairs are MRI, PET data sets and remaining are MRI and SPECT data sets. All the datasets have been collected from Harvard university library. In this framework four fusion metrics have been taken which are suitable for all fusion techniques. The four metrics are standard deviation, mutual information, universal image quality index, and tone mapped image quality index. All experiments were conducted in Matlab 2018b with a PC windows 10, 12GB RAM with 1 Terabyte.

#### 4.2 Abscition Studies

In the proposed work 3 parameters are used which are \( \tau, w_1 \) and \( w_2 \). Fused image causes color distortion when \( \tau = 4 \) and 5. But at \( \tau = 2 \) and 3 color distortion is low. The exact value of \( \tau \) which balances clarity and color fidelity is 3. The details of fused image vary with increase of \( w_1 \). Increase in \( w_2 \) sharpen the edges but there will be color distortion. After number of iterations, it is observed to set \( w_1=1.5, w_2=0.3, \) and \( \tau=3 \)

#### 4.3 Information Quantity Analysis

To test the efficacy of the present work, the number of non-zero pixels of OD, NOD, and HSI are counted. For a better decomposition, the number of non-zero pixels in total are high. Each pair of input images are decomposed into 4 overlapping, non-overlapping HSI images. So, a total of 120 non zero pixels are counted. The number of non-zero pixels of \( L^r_{\mu}, N^r_{\mu}, \) and \( O^r_{\mu} \) are counted and the ratio is also calculated. From this ratio, it is observed that, both OD and NOD images could acquire huge amount of information from HSI.

#### 4.4 LRD Analysis

To test the efficiency of the present algorithm, it is compared with three existing algorithms. Figure 2 shows the experimental indices of both MRI, PET and MRI, SPECT combinations. MRI contains structural information and each method gives detailed information. The only difference among all methods is color fidelity. Color fidelity of DWT, NSCT, and DTCWT-SR are observed to be
low. Compared to all methods, the proposed method is good at visual quality, local details, and fidelity. The execution time of the proposed method is moderate.

Figure 2. Experimental indices
Table 1. Experimental results

| Set No | Parameter | DWT       | NSCT      | DTCWT-SR | PROPOSED |
|--------|-----------|-----------|-----------|-----------|----------|
| Set-1  | STD       | 49.9173   | 49.5726   | 54.9935   | 63.0945  |
|        | MI        | 1.3792    | 1.3728    | 1.4027    | 1.6286   |
|        | UQI       | 0.6024    | 0.534     | 0.5091    | 0.6394   |
|        | TMQI      | 0.7000    | 0.7094    | 0.6948    | 0.7212   |
| Set-2  | STD       | 47.2363   | 47.1242   | 53.5543   | 60.1245  |
|        | MI        | 1.2279    | 1.3458    | 1.4126    | 1.5278   |
|        | UQI       | 0.5502    | 0.5640    | 0.5823    | 0.5924   |
|        | TMQI      | 0.6845    | 0.6867    | 0.6874    | 0.6901   |
| Set-3  | STD       | 48.2324   | 47.14     | 50.4712   | 55.2645  |
|        | MI        | 1.3224    | 1.3628    | 1.4027    | 1.5262   |
|        | UQI       | 0.5824    | 0.5894    | 0.6012    | 0.6124   |
|        | TMQI      | 0.6701    | 0.6800    | 0.6812    | 0.6820   |
| Set-4  | STD       | 47.5231   | 46.7812   | 51.2314   | 53.1247  |
|        | MI        | 1.3214    | 1.3478    | 1.3612    | 1.4423   |
|        | UQI       | 0.6214    | 0.6456    | 0.6625    | 0.6914   |
|        | TMQI      | 0.7124    | 0.7345    | 0.7612    | 0.7869   |

The Table 1 shows the objective analysis of different performance metrics of different methods and proposed method. The standard deviation of DWT is more compared to NSCT. Among all methods, the proposed method has high standard deviation. The proposed method has high mutual information, high universal quality index and high tone mapped quality index values compared to other methods.
Figure 3 shows the variation of different performance metrics. (a), (b), (c), and (d) represent Standard deviation, Mutual information, Universal quality index, and Tone mapped quality index respectively. Standard deviation, Mutual information, Universal quality index, and TMQI for first three sets of pairs of existing methods are close but, proposed method dominates all. For the fourth data set TMQI is observed in large variation.

5. CONCLUSIONS

In this paper, LRD for fusing medical images has been proposed. First, enhancement method for improving image was done and DGR algorithm was introduced. There are two problems in the existing methods. 1. Laplacian decomposition was failed to preserve the structural information. 2. The existing methods could not provide the redundant complementary information. In the proposed framework, OD and NOD fusion rules were used for redundant and complementary information respectively. Both these fusion rules make sure that high precision of fused image with high fidelity and high structural information has been achieved. IRS was presented to avoid artefacts caused in the reconstruction process of HSI images. The effectiveness of LRD was verified by implementing extensive experiments. Results demonstrate that, the proposed LRD has shown superiority compared to other methods subjectively and objectively, but, the running time must be considered. This can be still reduced by proposing rapid methods with efficient transform and effective fusion method in the future work.

References

[1] Y. Yang, Y. Que, S. Huang, and P. Lin, “Multiple visual features measurement with gradient domain guided filtering for multisensor image fusion,” 2017, IEEE Transactions on Instrumentation and Measurement, vol. 66, no. 4, pp. 691–703.

[2] A. P. James and B. V. Dasarathy, “Medical image fusion: A survey of the state of the art,” 2014, Information Fusion, vol. 19, pp. 4–19.

[3] P. Ganasala and V. Kumar, “Multimodality medical image fusion based on new features in nsst domain,” 2014, Biomedical Engineering Letters, vol. 4, no. 4, pp. 414–424.

[4] L. Meng, X. Guo, and H. Li, “Mri/ct fusion based on latent low rank representation and gradient transfer,” 2019, Biomedical Signal Processing and Control, vol. 53, p. 101536.

[5] G. Qi, J. Wang, Q. Zhang, F. Zeng, and Z. Zhu, “An integrated dictionary- learning entropy-based medical image fusion framework,” 2017, Future Internet, vol. 9, no. 4, p. 61.
[6] K. Wang, G. Qi, Z. Zhu, and Y. Chai, “A novel geometric dictionary construction approach for sparse representation based image fusion,” 2017, *Entropy*, vol. 19, no. 7, p. 306.

[7] H. Li, X. Li, Z. Yu, and C. Mao, “Multifocus image fusion by combining with mixed-order structure tensors and multiscale neighborhood,” 2016, *Inf. Sci.*, vols. 349–350, pp. 25–49, Jul.

[8] H. Li, H. Qiu, Z. Yu, and B. Li, “Multifocus image fusion via fixed window technique of multiscale images and non-local means filtering,” 2017, *Signal Process.*, vol. 138, pp. 71–85, Sep.

[9] Z. Zhu, Y. Chai, H. Yin, Y. Li, and Z. Liu, “A novel dictionary learning approach for multimodality medical image fusion,” 2016, *Neurocomputing*, vol. 214, pp. 471–482.

[10] Z. Zhu, H. Yin, Y. Chai, Y. Li, and G. Qi, “A novel multi-modality image fusion method based on image decomposition and sparse representation,” 2018, *Inf. Sci.*, vol. 432, pp. 516–529.

[11] Y. Liu and Z. Wang, “Simultaneous image fusion and denoising with adaptive sparse representation,” 2015, *IET Image Process.*, vol. 9, no. 5, pp. 347–357.

[12] M. Kim, D. K. Han, and H. Ko, “Joint patch clustering-based dictionary learning for multimodal image fusion,” 2016, *Inf. Fusion*, vol. 27, pp. 198–214, Jan.

[13] H. Li, X. He, D. Tao, Y. Tang, and R. Wang, “Joint medical image fusion, denoising and enhancement via discriminative low-rank sparse dictionaries learning,” 2018, *Pattern Recognit.*, vol. 79, pp. 130–146, Jul.

[14] M. Manchanda and R. Sharma, “An improved multimodal medical image fusion algorithm based on fuzzy transform,” 2018, *J. Vis. Commun. Image Represent.*, vol. 51, pp. 76–94.

[15] A. Baghaie, S. Schnell, A. Bakhshinejad, M. F. Fathi, R. M. D’Souza, and V. L. Rayz, “Curvelet transform-based volume fusion for correcting signal loss artifacts in time-of-flight magnetic resonance angiography data,” 2018, *Comput. Biol. Med.*, vol. 99, pp. 142–153.

[16] X. Liu, Y. Zhou, and J. Wang, “Image fusion based on shearlet transform and regional features,” 2014, *AEUE-Int. J. Electron. Commun.*, vol. 68, no. 6, pp. 471–477.

[17] Y. Li, Y. Sun, X. Huang, G. Qi, M. Zheng, and Z. Zhu, “An image fusion method based on sparse representation and sum modified-Laplacian in NSCT domain,” 2018, *Entropy*, vol. 20, no. 7, p. 522.

[18] X. Liu, Y. Zhou, and J. Wang, “Image fusion based on shearlet transform and regional features,” 2014, *AEUE-Int. J. Electron. Commun.*, vol. 68, no. 6, pp. 471–477.

[19] G. Qi, Q. Zhang, F. Zeng, J. Wang, and Z. Zhu, “Multi-focus image fusion via morphological similarity-based dictionary construction and sparse representation,” 2018, *CAAI Trans. Intell. Technol.*, vol. 3, no. 11, pp. 83–94.

[20] M. Yin, X. Liu, Y. Liu, and X. Chen, “Medical image fusion with parameter-adaptive pulse coupled neural network in nonsubsampled shearlet transform domain,” 2018, *IEEE Trans. Instrum. Meas.*, vol. 68, no. 1, pp. 49–64.

[21] Y. Liu, S. Liu, and Z. Wang, “A general framework for image fusion based on multi-scale transform and sparse representation,” 2015, *Inf. Fusion*, vol. 24, pp. 147–164.

[22] J. Du, W. Li, and B. Xiao, “Anatomical-functional image fusion by information of interest in local laplacian filtering domain,” 2017, *IEEE Trans. Image Process.*, vol. 26, no. 12, pp. 5855–5866.

[23] F. Shabanzade and H. Ghassemian, “Multimodal image fusion via sparse representation and clustering-based dictionary learning algorithm in nonsubsampled contourlet domain,” 2017, *Int. Symp. Telecommun.*, pp. 472–477.

[24] T. Li and Y. Wang, “Biological image fusion using a NSCT based variable-weight method,” 2011, *Inf. Fusion*, vol. 12, no. 2, pp. 85–92.

[25] G. Bhatnagar, Q. M. J. Wu, and Z. Liu, “A new contrast based multimodal medical image fusion framework,” 2015, *Neurocomputing*, vol. 157, pp. 143–152.

[26] P. Ganasala and V. Kumar, “CT and MR image fusion scheme in nonsubsampled contourlet transform domain,” 2014, *J. Digit. Imag.*, vol. 27, no. 3, pp. 407–418.

[27] Y. Li, Y. Sun, X. Huang, G. Qi, M. Zheng, and Z. Zhu, “An image fusion method based on sparse representation and sum modified-Laplacian in NSCT domain,” 2018, *Entropy*, vol. 20, no. 7, p. 522.
[28] A. Sahu, V. Bhateja, A. Krishn et al., “Medical image fusion with laplacian pyramids,” in 2014 International Conference on Medical Imaging, m-Health and Emerging Communication Systems (MedCom). IEEE, 2014, pp. 448–453.

[29] J. Du, W. Li, and B. Xiao, “Anatomical-functional image fusion by information of interest in local laplacian filtering domain,” 2017, IEEE Transactions on Image Processing, vol. 26, no. 12, pp. 5855–5866.

[30] X. Li, R. Nie, D. Zhou, and R. Xie, “Laplacian multi-scale medical image fusion algorithm for image enhancement,” 2019, Journal of Yunnan University: Natural Sciences Edition, vol. 41, no. 5, pp. 908–917.

[31] K. Koteswara Rao, K.Veera Swamy “Multomodal medical image fusion based on NSCT and DWT fusion framework” 2019, IJITEE vol. 9, no. 2.

[32] K. Koteswara Rao, K.Veera Swamy “Multimodal medical image fusion with Butterworth filter in NSCT domain based on dual fusion framework,” 2020, IJAST vol.29, no. 8, pp. 1363–1375.