Multimodal Biomedical Image Fusion Techniques in Transform and Spatial Domain: An Inclusive Survey

Nitin S. Thakare(✉) and Mukesh Yadav

Sage University, Indore, Madhya Pradesh, India
nit.thakare12@gmail.com

Abstract. Image of similar object can be taken by using several modalities at same/different time and in various environmental conditions. The human perception can extract same generalized information from captured images through different modalities. It is a need in clinical analysis to scientist, radiologist or practitioner to get right and exact information about captured image of different human body organ. Multimodal medical image fusion (MMIF) technique improves the resolution with minimum redundancy. This paper demonstrated a detail inclusive survey of multimodal image (MI) fusion (MIF) techniques from spatial domain to transform domain with different algorithm in biomedical field. In biomedical field diverse image fusion (IF) applications have been described. Each MIF techniques are evaluated based on output fused image quality by considering evaluation metrics. At last total review conclusion will be stated which will leave new research plan in the era of MIF.

Keywords: Multimodal · Image fusion (IF) · Decomposition

1 Introduction

There have been many proposed biomedical IF schemes in recent years due to the amount of research done on fusion of MI. By combining these approaches, algorithms are developed that improve the visual and information content of composite images. The advantages and limitations of different medical imaging modalities are different. Thus pathological tissue cannot be accurately reflected by a single mode medical image. A patient's condition is usually diagnosed by multiple doctors using different images of the same part, resulting in a complex and inaccurate diagnosis. Through the integration of reliable information from multimodal sources as much as possible, MMIF seeks to detect and serve diseases accurately and comprehensively [2]. The IF merges the features of many input images one image that becomes more suitable and easier to get the information for clinical analysis. The fusion of images can be applied to many fields, including artificial intelligence, pattern recognition, computer vision, machine learning, and image processing. In spatial domain the fusion of MI usually affected by low contrast while in transform domain the fused image get degraded with respect to

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information content [5]. Fusion of image can be done in spatial, transform domain and combination of both domain (spatial and transform) may be called as hybrid domain.

2 Context

2.1 Different Medical Modalities Used in IF

In this segment of article presents several medical modalities used to scan the body of human according to need of patients treatment like Computerized Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT) and Electrocardiography (ECG) [4] are used as source images for fusion. CT scans are excellent for locating lesions and providing a broad range of anatomical and hard tissue information, but they provide a significant amount of information regarding soft tissues and bone tissues. Images from MRI can depict architect of soft tissues, but it has difficulties detecting bone tissue information [2]. PET and SPECT images do not contain anatomical information, and they are used as a way to visualize tissue function with functional flow or their cellular working in a low spatial resolution [29]. X-ray provides information about the connectivity and integrity of bones of human body. CT, MRI and X-ray provide architectural information while PET and SPECT provide efficacious information of human body [2]. Following Fig. 2 shows examples of each modality those are the images captured by different machines.

Multimodal Image Fusion
Ultimate aim of the MIF of different modality is to get a single image with more content and reduce the repetitive information, to increase chromatic appearance regarding sharpness and clarity [5], to reduce the blurring, to preserve spectral content from spatial domain [24]. Image fusion is method of combining the different images captured by different sources which illustrate the required information of all source images. MF is a fusion of more than two images of similar object captured by different imaging device [5]. Details provided by MRI, CT and SPECT, PET can be amalgamate in one image this is known as IF. Following figure shows in general fusion of image (Fig. 1).

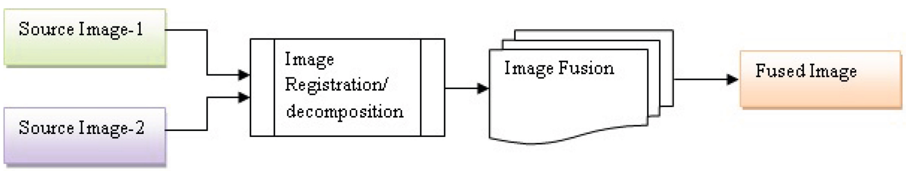


Fig. 1. IF Block Diagram

Applications
Image fusion has wide variety of applications in field of biomedical diagnosis, terrestrial image sensing, security surveillance, photography. In this article we are focusing on MIF

in biomedical applications only. It is possible to combine different medical modalities such as MRI-PET, MRI-CT, MRI-SPECT [24] into one image to diagnose a patient's conditions by creating a fused image. Figure 2 shows example MMIF, Fig. 2a shows fusion of MRI/CT modality where visual appearance is a better in terms of structure [5]. Figure 2b and c shows fusion of MRI/PET and MRI/SPECT modality respectively where details and visual status of fused image are enhance with low detail degradation [24].

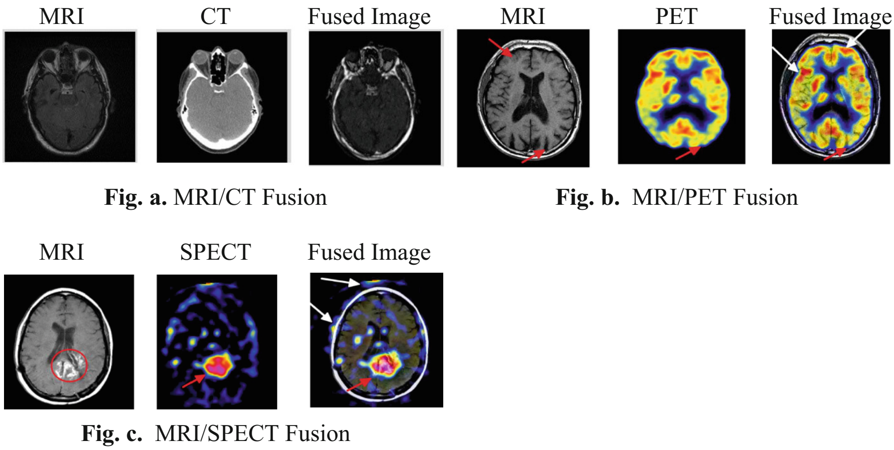


Fig. 2. MIF (a): MRI/CT, (b): MRI/PET, (c): MRI/SPECT

3 Image Fusion Method

Fusion can take place in the spatial and transform domains. Figure 3 shows details of existing IF methods [16, 18, 31].

3.1 Related Work of Image Fusion in Spatial and Transform Domain

Zhiqin Zhu et al. present the method for fusion of multimodal image with preserving structural and detailed information of source image. Spatial-based method and sparse-representation (SR) based method is proposed for multimodal image decomposition into cartoon and texture components respectively using Vese–Osher (VO) model. [17]. Chunyang Pei et al. presents study of fusion of images where the guided filter used for two scale decomposition to improve edge information using Laplacian Pyramid Decomposition (LRD). Due to the dictionary learning process involved in the presented framework, the process may take a considerable amount of time. In both visual effect and objective evaluation, the proposed method is good [7]. Dheeraj Kandikattu et al. proposed study on Linear Weighted MIF where information map of source image is derived using convolution sets [1]. Lifang Wang et al. presented research on the MMIF based on Gabor representation combination of multi-CNN and fuzzy neural network [2].

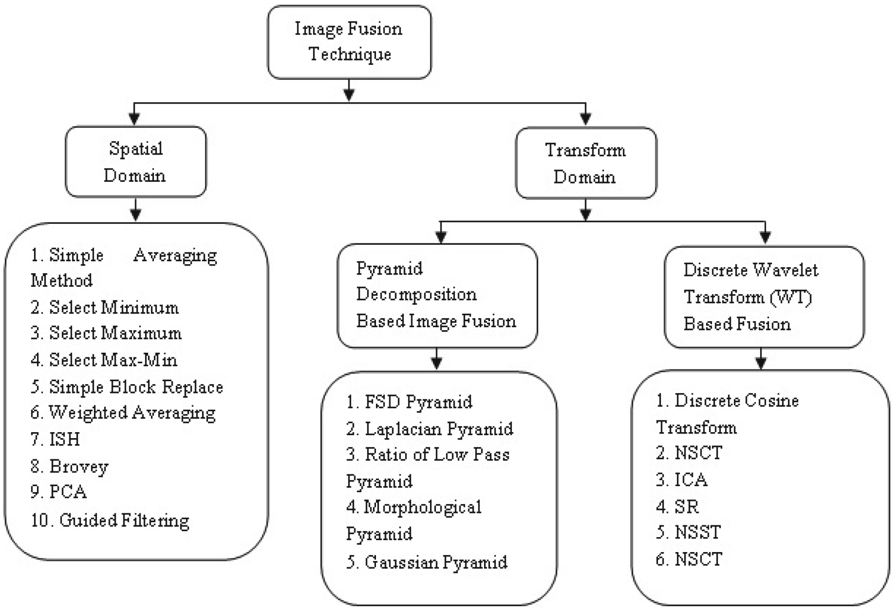


Fig. 3. Fusion Methods

Figure 3 shows details of existing IF methods [16, 18, 31].

This article present a work on regional MMIF method based on superpixel segmentation which provides more homogeneous regions. To obtain texture and contrast feature the Log-Gabor filter and sum modified Laplacian (SML) [3] are used. Rencan Nie et al. put forward a study on new structure to fuse multimodal medical images, based on multi-source information exchange encoding (MIEE) by using Pulse Coupled Neural Network (PCCN) [4] where two fusion processes is performed in two steps to optimize nonlinear transformation parameter. [4].

Muhammad et al. put forward the method to fuse of CT & MRI modality of the brain by adaptive pixel fusion algorithm where noise in each pixel is removed by noise controlling coefficients. New adaptive weights are calculated with the help of noise controlling coefficient. [5]. Yong Yang et al. put a works on novel MMIF method where input images decomposed into base and salient elements by decomposition. Fused image is obtained by combining the fused base and saliency parts [6]. This paper presents a framework for implementing MIF using Non Non-subsampled Shearlet Transform (NSST) [8] and SR. After decomposition of the source image, low frequency components are fused using the SR model and the high frequency components are merged using guided filtering [8]. In order to deal with concerns such as degraded edges, extra details, and max spatial distortion due to poor contrast, this paper present a novel approach for decomposing CT and MRI images using Convolutional Sparse Image Decomposition (CSID) [9]. Xiaoxiao Li et al. proposed a study on fusion of multi modal images using Laplacian redecomposition, overlapping domain (OD) fusion rule and non overlapping (NOD) fusion rule [10] to resolve the issues of retaining image structure information, identify redundant information and integrate complementary information respectively [10].

C.S. Asha et al. presents the study of MMIF method using NSST and (chaotic grey wolf optimization) CGWO algorithm. NSST and CGWO provide advantage of fast convergence speed with less iteration over GWO algorithm. Method has more computational complexity as compared to most of the methods [11].

Ming Yin et al. presents the study of fusion of multimodal medical image using in non NSST domain with parameter-adaptive PCCN (PA-PCNN) [12], to fuse the high-frequency coefficients with all the PCNN variables adaptively calculated based on input bands that removes the limitation of PCNN model of difficulty of setting free parameters. To fuse of low content coefficients the weighted local energy (WLE) and weighted sum of eight-neighborhood-based modified Laplacian (WSEML) methods are used for energy preservation and detail extraction respectively [12]. Ebenezer Daniel proposed homomorphic MMIF technique using Hybrid Genetic Grey Wolf Optimization (HG-GWO) overcome the limitation of GWO such as static scales selection and randomly selected control elements [13]. Lu Tang et al. presents the study of guided adaptive optimization method to automatically determine the optimal parameters for fusing multimodal medical images based on PCNN optimized by multi-swarm fruit fly optimization algorithm (MFOA) [14], to overcome the limitation of traditional PCNN and fly optimization algorithm (FOA) [14], such as setting the parameter adaptively and limited space search respectively. Objective numerical & visual analysis shows proposed method conserve max boundary, details and texture content with higher contrast and sharpness [14].

Using advanced image decomposition and image fusion strategy, Jiao Du et al. put forward study to fuse MI. Local Laplacian filtering (LLF) algorithm is used for decomposition. The proposed method has some limitations like LLF is slow filtering & use of IOI captures less color information [15].

Rui Zhu et al. present a study of composite decomposition model for MMI (MRI-CT) in NSST domain with two fusion strategy sum of modified Laplacian (SML) and modified choosing maximum (MCM). These work reserve texture content of MRI and bone information of CT images except preservation of edge information [16].

This article comes with work of fusion of image based on SR, where researcher addresses convolutional sparse (CSR) representation to conquer the limitation of SR-based fusion algorithms. It is observed that CSR-based methods improves the fusion performance when increasing the number of dictionary filters, but numerical differences are comparatively less, especially when there are more than 31 dictionary filters [18].

Yong Yang et al. proposed the research study of MMIF where two different modalities are fragmented into series of high frequency components & single low frequency component. After decomposition, type-2 fuzzy fuse strategy is used to fuse high content components and local energy algorithm to fuse low content components. It is observed that results of proposed method are highly better in term of MI and SD while in terms of Edge Based Similarity Measure performance is quite good than other methods. Proposed method can achieve the better performance for medical image modalities than areas of applications [19]. Ali-Reza Mohammadi et al. proposes a structured and sparse canonical correlation analysis (ssCCA) technique as a advanced CCA method to conquer limitation such as loss of spatial content, like high-dimensionality, multi-collinearity, unimodal feature selection and asymmetry of present CCA based fusion methods [20].

Vikrant Bhateja et al. presents the study for fusion of MRI and CT-Scan using cascaded combination of stationary wavelet Transform (SWT) and Non-Subsampled Counterlet Transform (NSCT) for betterment of shift variance, directionality [21] and phase information in fused image. To reduce the redundancy of modalities principal component analysis (PCA) in SWT domain is used. To maximize the contrast of fused image, the maximum fusion rule in NSCT domain is used**.** Researcher applies the SWT as SWT detects the curved shapes more precisely than DWT and also provides better time and frequency localization but also, but processing via SWT leads to non-directionality in the decomposed component highly. To remove this lacuna, PCA based fusion rule is used as it is a highly directional and counters the non-directionality limitation of SWT but then it leads to shift variance of SWT. To conquer this issue, NSCT is used which is a highly shift invariant transform [21]. This paper presents the study of fusion techniques of multimodality medical image in frequency domain. For fusion of MRI & CT sets the multimodal images are registered by geometric transformation like translation or shifting, scaling and rotation transformation to align the pixels [22].

Researcher present the method for classification of lung needle biopsy images using multimodal SR. Proposed method goes through three phases, first phase take outs the features for cell nuclei in lung needle biopsy images using data acquisition. The second phase is training where three learning sub-dictionaries are created on the basis of shape, color, and texture of individual lung cell nuclei information which is already available in first phase of data acquisition [23].

In this paper a fusion of multimodal images is stated where source images are decomposed by NSCT This study illustrates how to use phase congruency which is a first fusion rule to achieve representation of low-frequency components without variation in brightness and contrast. Also second fusion rule based on directive contrast in which the many important texture information and edge information is retained. Distortions in spectral & color information are overcome by proposed method and preserves spectral content and also enhance the spatial contents than the existing algorithms [24]. Fusion of CT and PET images on the basis of mutual information is presented in this research paper. Mutual information represents to extracting most relevant specific information of input image data sets. By setting a channel of information between two images, different information-based algorithms are used to select the most informative voxel from the input data sets based on different information measure associated with pixel intensity. [25]. Xiaojun Xu et al. present study for MMIF using discrete fractional wavelet (DFRWT) which address the issues occurs in DFT, LP, Contourlet transform, NSCT [26]. This article present study of MIF using improved PCNN convolutional SR in NSST domain to address the issue of integrity of fusion, edge information and processing of the edge points [27]. Cheng-I Chen present the study to fuse of PET and MRI modality using ISH model and log-Gabor wavelet transform to combine both anatomical structures with metabolic changes into single fused image. In this paper, the authors present a hybrid model in which two fusion strategies are used to fuse multimodal images with the purpose of minimizing color distortion as much as possible [28]. It is discussed in this paper how NSCT and PCNN can be combined to generate fused images with max contrast, visibility and data content based on subtle differences in the source medical images [29] (Table 1). Table 2 illustrate the classification of image fusion methods.

Table 1. IF in spatial and transform

Multimodal Medical Image	Basic Method	Fusion Rule	Decomposition/Transform /Spatial Domain	Applications
PET-MRI and SPECT-MRI [17], [7]	Multi-scale Decomposition Method (MSD)	OMP algorithm and Max-L	SR	Brain Diagnosis
	Hybrid Method	LP-SR and Guided Filtering Based	LRD, position and Dictionary Learning	
MRI-CT [1]	Pixel level fusion	Weighted Average Fusion	Spatial Domain	
MRI-CT [2]	MSD	Maximum fusion rule (MFR)	Log Gobar	Brain cerebral infection
MRI-CT [5]	Adaptive pixel fusion algorithm	Gradient compass	Spatial Domain	Brain Diagnosis
MRI-CT [8]	Multi-scale Geometric Analysis	SR based and Guided Filtering	NSST and sparse K-SVD dictionary	
MRI-CT [9]	Multi-scale Decomposition Method	SR-based L1 norm fusion	CSID	
MRI-CT [12]	Multiscale and multidirection decomposition	PA-PCNN, WLE and WSEML	NSST	
MRI-CT [16]	Hybrid Method	MCM, SML	NSST	
MRI-CT [21]	Hybrid methods	PCA based Fusion and Maximum fusion rule in NSCT domain	NSCT, SWT	Analysis of interested area and soft, dense tissue of brain
MRI-CT [30]	Hybrid Method	Maximum Selection and modified spatial frequency (MSF) using PCNN in NSCT	NSCT	
MRI-CT, PET-SPECT [6]	Pixel level fusion	WLEMM, improved SF and L-2	Spatial Domain	Brain Diagnosis
MRI-SPECT,MRI-PET [10]	MSD	OD, NOD and local energy maximum	LRD	Brain Diagnosis
MR-SPECT, MR-PET, MR-CT [11, 13, 19]	MSD with CGWO Algorithm	Maximum fusion rule and adaptively weighted fusion technique	NSST	Glioma tumor in brain

(continued)

Table 1. (*continued*)

Multimodal Medical Image	Basic Method	Fusion Rule	Decomposition/Transform /Spatial Domain	Applications
	MSD	Pixel based averaging rule, OHWF using HG-GWO in DWT	Discrete Wavelet Transform (DWT)	Brain diagnosis
	MSD	Type-2 fuzzy based fusion rule and local energy algorithm	NSCT	Tumor Detection
MRI-PET, MRI-SPECT (15)	MSD	LEM scheme	LLF	Brain diagnosis
Biomedical Image [18]	SR	CSR, Choose Max Fusion Rule,	Two Scale decomposition	Brain Tissue Observance
f-MRI, s-MRI [20]	SR	Structured and Sparse CCA based	Singular value decomposition	Alzheimer's disease
PET-MRI, SPECT-MRI [24]	Multiscale Geometric Analysis	Phase congruency based model and directive contrast in NSCT domain	NSCT, SML	Brain with Alzheimer
CT-PET [25]	Pixel level fusion	Symmetric fusion strategy	Spatial Domain	Brain Diagnosis
MRI-PET [26]	Multiresolution methods	Weighted fusion rule	DFRWT	
MRI-PET [28]	Hybrid Method	Maximum Selection and weighted averaging fusion strategy	IHS and Log-Gabor Wavelet Transforms	Alzheimer's disease brain images

4 Insights and Limitations of Existing Image Fusion Methods with Function of Fusion Rule

Several methods listed in Fig. 3 are used to fuse multimodal images those are having its own advantages and limitations. A common consequence of fusion methods in the spatial domain like PCA and intensity color saturation (ISH) is that the image is frequently distorted spectrally and spatially, making it difficult for the doctor to make a decision [2]. Pixel level spatial domain methods courses contrast reduction and it is more effective to use applications that use ISH, PCA and the Brovey transform but it shows spectral degradation [29]. The decomposition process of pyramidal IF schemes lack any spatial orientation selectiveness, which leads to blocking effects [31]. IF in spatial domain has advantage of presentation of good spatial content. Pyramid-based and wavelet transform based methods are belongs to transform domain methods. Laplacian pyramids, Gaussian pyramids, contrast pyramids, and morphological pyramids are all pyramid transformations based on spatial direction selectivity, however, spatial direction selectivity [32] is not included during the decomposition process, which results in block effects. Moreover, they produce antiquity at the edge of a fused image, which negatively impacts the fusion result [32].

Table 2. Different fusion rule

Fusion Technique/Algorithm	Domain	Function
LP-SR based [7]	Transform	Preserve the structural information and energy of the image
Guided filtering-based strategy [7]	Transform	Spatial consistency is maintained through noise filtering, and meaningless details are excluded
OD, NOD and local energy maximum (LEM) [10]	Transform	Removes redundant information, color distortion
Averaging [13]	Spatial	Reducing contrast and distortions in the fused images
PCA [21]	Transform	Improves feature enhancements and reduces data similarity
Maximum fusion in NSCT Domain [21]	Transform	Improves contrast and morphological details
Directive contrasts [24]	Transform	Edges, lines, and region boundaries can be extracted, but they are very sensitive to noise
Phase congruency [24]	Transform	Localizes image features more accurately
Max Selection and MSF using PCNN in NSCT domain [30]	Hybrid	Captures the properties of PCNN, MSF and NSCT like less degrading effects and differences to the original images, it captures the subtle differences and details without reducing contrast, while maintaining high spatial resolution
PCA based Fusion and Maximum fusion rule in NSCT domain [21]	Hybrid	Dimensionality reduction

5 Objectively Quality Evaluation Metrics

Evaluation of quality of output fused image on the basis of some quality assessment metrics is very important in image fusion applications. Table 3 describes different quality metrics with their function and Table 4. Shows qualitative analysis of CT-MRI modality fusion in transform and spatial domain (Tables 5, 6 and 7).

Table 3. Quality Evaluation Metrics

Metrics	Function
Feature mutual information (MI) [1, 2, 5–7, 11–15, 17, 19, 24, 26, 30, 31]	Provide index of source and fused images for the same features
Visual information fidelity (VIF) [17]	Using Human Visual System (HVS) model, VIF quantifies the mutual information between reference and test images
Gradient Metric [4, 7, 14, 18] Quality Metric [1]	Provide index of edge information is inherited from the input images to the FI
Standard Deviation [2, 7, 10–12, 14, 15, 19, 21, 22, 26, 30] Average pixel intensity(API) [5, 13]	Quantified the general contrast of a fused image and higher value indicate high contrast
Detect Correct Similarity (DCS), edge information retention, edge strength [1, 2, 6, 11, 13, 15–19, 24, 29–31]	DCS provides the similarity between the edge pixels of source and output image Measures the edge details of input source images compared with the output fused image
Structural Similarity Index (SSIM) [1, 4–6, 12, 15, 16, 21, 24]	Measures structural similarity by considering contrast, variance and luminance
Feature Similarity Index (FSIM) [4]	Evaluate the image local quality based on phase congruency and gradient magnitude
Entropy (H) [5, 12, 13, 18, 21, 22, 30]	Provide index of information is encapsulated in fused image, greater value indicate maximum information
Peak Signal-to-Noise Ratio [21]	Large value means good PSNR in fused image
Average gradient (AG) [5, 15]	Provide a level of sharpness and clarity
Correlation coefficient (CC) [5, 22]	Provides correlation index
Fusion symmetry (FS) [5]	Provides similarity index of information in the fused and source medical images
Total information transfer[5]	Measures transferred and lost information
Visual information fidelity fusion (VIFF) [10, 12, 15]	Measures observational information fidelity between input and fused image
Tone-mapped image quality index (TMQI) [15]	Measures structural and statistical information transfer from the anatomical image (MRI) and functional image (PET and SPECT) into fused image
Nonlinear correlation information entropy (NCIE) [16]	Measures nonlinear correlation
Cross Entropy (CEn) [22]	Measure of dissimilarity between source and fused image

(*continued*)

Table 3. (*continued*)

Metrics	Function
Average Gradient (AG) [28]	Measures spatial quality by estimating gradient in RGB component of fused image
Average Standard Deviation (ASD) [28]	Measures spatial quality by estimating SD in RGB component of fused image
Spatial Frequency(SF) [29, 31]	Measure the overall activity and clarity

Table 4. Quantitative Analysis of CT-MRI Modality Fusion in Transform and Spatial domain

Fusion Rule	Domain	MI/FMI	SD	Edge Similarity/Strength	Entropy	Gradient
Log Gobar [2]	Transform	3.8849	62.32	0.8652	NI	NI
OMP algorithm and Max-L [7]		NI	85.4193	NI	NI	0.5431
SR based and Guided Filtering [8]		3.4027 ± 0.2128	89.49 ± 3.8922	0.5851 ± 0.0438	5.5652 ± 0.2011	
SR-based L1 norm fusion [9]		3.9649	NI	0.8021	6.9971	NI
MFR and adaptively weighted fusion technique [11]		NI	85.9182	NI	5.7434	NI
Pixel based averaging rule, OHWF using HG-GWO [13]		4.0723	81.5372	0.1816	5.3854	NI

(*continued*)

Table 4. (*continued*)

Fusion Rule	Domain	MI/FMI	SD	Edge Similarity/Strength	Entropy	Gradient
Adaptive pixel fusion algorithm in spatial domain [3]	Spatial	5.96*	NI	0.6956*	NI	0.0695*
Adaptive pixel fusion algorithm [5]		NI	NI	0.5942*	4.4913*	NI
Pixel Level Fusion [6]		3.9566		0.7557		
Pixel Level Fusion [1]		NI	NI	NI	NI	1.0914
Type-2 fuzzy based fusion rule and local energy algorithm [19]	Hybrid	3.9635	90.1086	0.6412	NI	NI
Fusion rely on PCA [21]		NI	74.1232	0.8588	6.9414	NI
Maximum Selection and MSF using PCNN in NSCT domain [30]		3.94	74.7841	0.6554	5.5684	NI

Note: * indicate average of measure of more than one test data set
NI – Not Indicated.

Table 5. Subjective Analysis of MRI-CT IF in Spatial Domain Methods

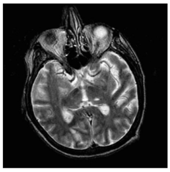
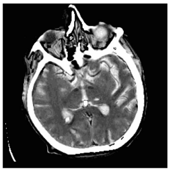
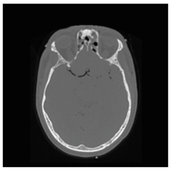
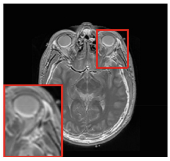
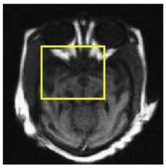
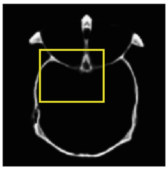
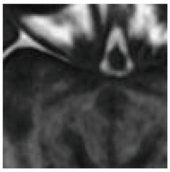
Spatial Domain Fusion Rule/ Strategy	Medical Multimodal Source Image		Fused Image
	MRI	CT	
Weighted Average Fusion [1]			
Maximum Fusion[2]			
WLEMM, improved SF and L-2 [6]			

Table 6. Subjective Analysis of MRI-CT IF in Transform Domain Methods

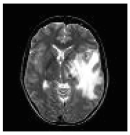
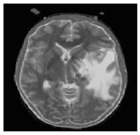
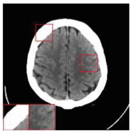
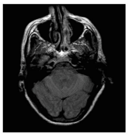
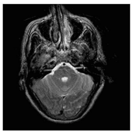
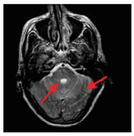
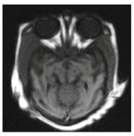
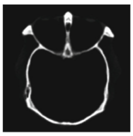
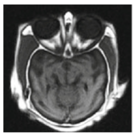
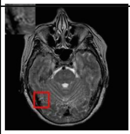
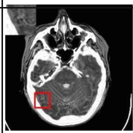
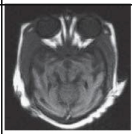
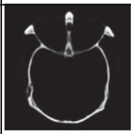
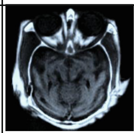
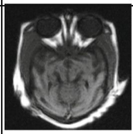
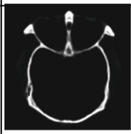
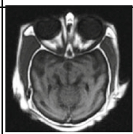
Spatial Domain Fusion Rule/ Strategy	Medical Multimodal Source Image		Fused Image
	MRI	CT	
OHWF using HG-GWO in DWT [13]			
PA-PCNN, WLE and WSEML in NSST domain [12]			
phase congruency based model and directive contrast in NSCT domain [24]			
Maximum Selection and MSF using PCNN in NSCT domain [30]			

Table 7. Subjective Analysis of MRI-CT IF in hybrid Domain Methods

Transform Domain Fusion Rule/Strategy	Medical Multimodal Source Image		Fused Image
	MRI	CT	
MCM, SML [16]			
PCA based Fusion and Maximum fusion rule in NSCT domain [21]			
Maximum Selection and MSF using PCNN in NSCT domain [31]			

6 Conclusion and Future Scope

Fusion of multimodal medical images aims to combine all relevant information from different images into a single image with proper enhancement and without compromising information. With the advancement of fusion techniques, it will be possible to diagnose patients more accurately. The purpose of this article is to provide a survey of various techniques of image fusion at the spatial and transform domain and combination of both domains with proper decomposition method. It has been observed from the literature review that the standard of MIF rely on the choice of decomposition method and fusion rule and fusion in spatial domain is relatively straightforward with low computational complexity, but suffers from spatial distortion, contrast imbalance, color distortion, while in a transform domain the fused image gets degraded relative to information content with high computational complexity, requiring large memory. By comparing the performance of various fusion methods based on quality metric check in both domains, it can be concluded that output fused image using transform domain having superior quality than fusion in spatial domain. Further the coefficient selection enhancement in sub scale space for spectral level coefficient selection in fusion of multimodal medical image can be achieved in transform domain.

References

1. Rajangam, V., et al.: Texture aware deep feature map based linear weighted medical image fusion. IEEE Access **10**(7), 88787–88797 (2022)
2. Wang, L., Zhang, J., Liu, Y., Mi, J., Zhang, J.: Multimodal medical image fusion based on Gabor representation combination of multi-CNN and fuzzy neural network. IEEE Access **9**, 67634–67647 (2021). https://doi.org/10.1109/ACCESS.2021.3075953

3. Duan, J.W., Mao, S.Q., Jin, J.W., Zhou, Z.G., Long Chen, C.L., Chen, P.: A novel GA-based optimized approach for regional multimodal medical image fusion with superpixel segmentation. IEEE Access **9**, 96353–96366 (2021). https://doi.org/10.1109/ACCESS.2021.3094972
4. Nie, R.: Multi-source information exchange encoding with PCNN for medical image fusion. IEEE Access **31**(3), 986–1000 (2021)
5. Irshad, M.T.: Gradient compass-based adaptive multimodal medical image fusion. IEEE Access **9**, 22662–22670 (2021)
6. Yang, Y.: Multimodal medical image fusion based on weighted local energy matching measurement. IEEE Access **70**, 1–16 (2021)
7. Pei, C.: Two-scale multimodal medical image fusion based on guided filtering and sparse representation. IEEE Access **8**, 140216–140233 (2020)
8. Singh, S.: Multimodal medical image sensor fusion model using sparse K-SVD dictionary learning in nonsubsampled shearlet domain. IEEE Access **69**(2), 593–607 (2020)
9. Muzammil, S.R.: CSID: a novel multimodal image fusion algorithm for enhanced clinical diagnosis. Diagnostics **10**(11), 904 (2020)
10. Li, X., Guo, X.: Laplacian redecomposition for multimodal medical image fusion. IEEE Trans. Instrum. Meas. **69**(9), 6880–6890 (2020)
11. Asha, C.S.: Multi-modal medical image fusion with adaptive weighted combination of NSST bands using chaotic grey wolf optimization. IEEE Access **7**, 40782–40796 (2019)
12. Yin, M.: Medical image fusion with parameter-adaptive pulse coupled neural network in nonsubsampled Shearlet transform domain. IEEE Trans. Instrum. Meas. **68**(1), 49–64 (2019)
13. Daniel, E.: Optimum wavelet-based homomorphic medical image fusion using hybrid genetic-grey wolf optimization algorithm. IEEE Sensors J. **18**(16), 6804–6811 (2018)
14. Tang, L.: Exploiting quality-guided adaptive optimization for fusing multimodal medical images. IEEE Access **7**, 96048–96059 (2019)
15. Du, J.: Anatomical-functional image fusion by information of interest in local Laplacian filtering domain. IEEE Trans. Image Process. **26**(12), 5855–5866 (2017)
16. Zhu, R.: HID: the hybrid image decomposition model for MRI and CT fusion. IEEE J. Biomed. Health Inform. **26**(2), 727–739 (2022)
17. Zhu, Z.: A novel multi-modality image fusion method based on image decomposition and sparse representation. Inf. Sci. **432**, 516–529 (2018)
18. Liu, Y.: Image fusion with convolutional sparse representation. IEEE Signal Process. Lett. **23**(12), 1882–1886 (2016)
19. Yang, Y.: Multimodal sensor medical image fusion based on type-2 fuzzy logic in NSCT domain. IEEE Sensors J. **16**(10), 3735–3745 (2016)
20. Mohammadi-Nejad, A.R.: Structured and sparse canonical correlation analysis as a brain-wide multi-modal data fusion approach. IEEE Trans. Med. Imaging **36**(7), 1438–1448 (2017)
21. Bhateja, V.: Multimodal medical image sensor fusion framework using cascade of wavelet and Contourlet transform domains. IEEE J. **15**(12), 6783–6790 (2015)
22. Chavan, S.S., Talbar, S.N.: Multimodality image fusion in frequency domain for radiation therapy. In: International Conference on Medical Imaging, m-Health and Emerging Communication Systems (MedCom), pp. 174–178 (2014)
23. Shi, Y.: Multimodal sparse representation-based classification for lung needle biopsy images. IEEE Trans. Biomed. Eng. **60**(10), 2675–2685 (2013)
24. Bhatnagar, G.: Directive contrast based multimodal medical image fusion in NSCT domain. IEEE Trans. Multimedia **15**(5), 1014–1024 (2013)
25. Bramon, R.: Multimodal data fusion based on mutual information. IEEE Trans. Visual. Comput. Graph. **18**(9), 1574–1587 (2012)
26. Xu, X.: Medical image fusion using discrete fractional wavelet transform. Biomed. Signal Process. Control **27**, 103–111 (2016)

27. Shen, S., Wang, W.: Multimodal image fusion based on improved pulse-coupled neural network and convolutional sparse representation in NSST domain. In: IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), pp. 1295–1300 (2021)
28. Chen, C.I.: Fusion of PET and MR brain images based on IHS and Log-Gabor transforms. IEEE Sensors J. **17**(21), 6995–7010 (2017)
29. Nobariyan, B.K., Daneshvar, S.: Fusion of SPECT and MRI images using back and fore ground information. In: 8th Iranian Conference on Machine Vision and Image Processing (MVIP), pp. 227–231 (2013)
30. Das, S.: NSCT-based multimodal medical image fusion using pulse-coupled neural network and modified spatial frequency. Med. Biol. Eng. Comput. **50**(10), 1105–1114 (2012)
31. Das, S.: A neuro-Fuzzy approach for medical image fusion. IEEE Trans. Biomed. Eng. **60**(12), 3347–3353 (2013)
32. Du, J., Li, W., Lu, K., Xiao, B.: An overview of multi-modal medical image fusion. Neurocomputing **215**, 3–20 (2016)