

Advancements In Multi-Modality Medical Image Fusion: A Comprehensive Review

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ABSTRACT– Multimodality medical image fusion involves the amalgamation of multiple images acquired through single or multiple imaging modalities. The purpose of medical image fusion methods is to enhance the quality of medical images by effectively capturing the key features within the fused output. This consequently enhances the practicality of medical images for diagnostic assessment and issue identification. Medical imaging modalities like magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) have been developed and are extensively utilized for clinical diagnoses. These multimodality images harbor vital information crucial for precise and efficient diagnosis of brain ailments. As a result, amalgamating diverse image modalities in the medical domain to create a distinct image brimming with intricate anatomical details and heightened spectral information has become exceedingly valuable in clinical diagnosis. This manuscript offers an exhaustive examination of existing literature on image fusion, elucidating the fundamental concepts and materials essential for a comprehensive grasp of diverse medical fusion techniques.

KEYWORDS – Medical Image Fusion, DCT, DWT, PCA, Multimodality

I. INTRODUCTION

Image fusion involves the amalgamation of images captured by sensors operating at distinct wavelengths, all simultaneously observing the same scene. The purpose is to create a unified composite image [1]. This composite image is constructed to enhance the content of the image and facilitate user tasks such as target detection, recognition, identification, and bolstered situational awareness. The process of image fusion entails the analysis of multiple images of the same scene or objects, extracting crucial data from each, and synthesizing it into a singular output image [2]. The resultant image yielded by this approach consistently offers a greater wealth of information compared to any individual input image, thereby elevating data quality and its practical utility. The interpretation of "quality" hinges on the specific application domain. In recent times, significant advancements have been made in image acquisition techniques [3]. State-of-the-art technologies in image capturing devices empower us to extract diverse sets

of information from a single image. This amassed information can be effectively amalgamated using the technique of "fusion" to generate an image enriched with heightened informativeness.

Image fusion offers an effective solution to manage the escalating influx of data, concurrently extracting valuable insights from the source images [4]. The amalgamation of data from multiple sensors often supplies complementary information concerning the surveyed area, rendering image fusion an efficacious tool for facilitating comparison and analysis of such data [5]. It's noteworthy that image fusion isn't confined to multi-sensor scenarios; it holds significance across both single-sensor and multi-sensor applications. Figure 1 illustrates the fusion of MRI and CT images.

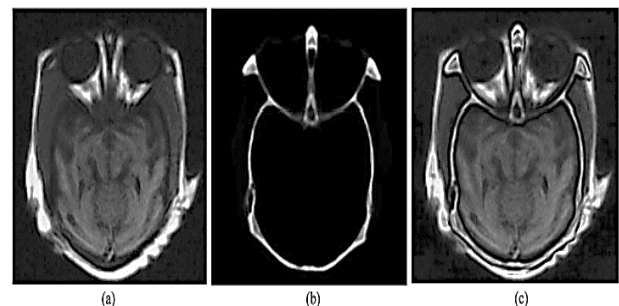


Figure 1: Examples of Image Fusion (a) MRI Image (b) CT Image (c) Fused image

Within image processing, image fusion denotes the process of merging several images of the same scene or subject to craft a composite image that surpasses any individual input image in terms of information or features [6]. The objective is to distill pertinent information from each input image, culminating in a singular image that presents a comprehensive and aesthetically pleasing rendition of the scene. The rationales for conducting image fusion are discussed below:

- Enhancing image quality- Image fusion can heighten image quality by merging images with diverse attributes, such as distinct exposures or focus points. This confluence can engender a resultant fused image

endowed with augmented brightness, contrast, and sharpness.

- Increasing information content- Fusion of multiple images can assimilate supplementary data potentially absent in individual images. This encompasses the fusion of images captured by disparate sensors or modalities, like infrared and visible light images, to unveil concealed intricacies or enhance scene comprehension.
- Noise reduction- Image fusion serves as a strategy to curtail noise or artifacts prevalent in individual images. The synthesis of multiple noisy images permits the application of statistical averaging or filtering techniques to mitigate noise, thereby amplifying the signal-to-noise ratio within the fused image.
- Diverse approaches to image fusion exist, contingent upon the application and prerequisites [7]. Notable techniques encompass:
 - Pixel-based fusion- This strategy entails pixel-level operations, such as averaging or weighted averaging, applied to corresponding pixels from input images, generating the fused image. Although straightforward, it might neglect fine details or fail to accommodate misalignments between input images.
 - Feature-based fusion- This approach involves extracting specific features or regions of interest from each input image and merging them to formulate the fused image. It's advantageous when certain features are more prominent or relevant in different input images. Techniques span edge detection, texture analysis, and object detection.
 - Transform-based fusion- This methodology applies mathematical transforms, like wavelet transforms or Fourier transforms, to disintegrate input images into diverse frequency or spatial domains. The transformed representations are then combined to yield the ultimate image. Transform-based fusion methods afford better control over the fusion process and can address assorted image characteristics.

Image fusion manifests its utility across domains such as remote sensing, medical imaging, surveillance, and computer vision. By harmonizing information from diverse sources or modalities, it propels improved analysis, interpretation, and decision-making.

II. MULTI MODALITY MEDICAL IMAGE FUSION

Multi-modality medical image fusion (MMIF) is commonly defined as the process of amalgamating two or more geometrically aligned images from single or multiple modalities [8]. The primary objective is to create a composite fused image with heightened quality and prominent features. Fusion scenarios are grouped into four classes:

- Multi-temporal Fusion- This approach captures the same scene at different time points. Long and short-term observations are necessary to assess changes on the ground. Given the diverse timing of observations from revisit satellites in remote sensing, multi-temporal

images are crucial for identifying land surface alterations across extensive geographic regions.

- Multi-view Fusion- Multi-view images encompass distinct perspectives captured simultaneously. This is also termed Mono-modal fusion [9]. Existing methods might not consistently yield satisfactory results, particularly when one of the estimations lacks quality, rendering them unable to effectively discard such estimations.
- Multi-focus Fusion- This method efficiently combines information from several images with comparable viewpoints into a comprehensive image. The resultant composite image is more informative than its input counterparts [10], resulting in enhanced visual quality.
- Multi-modality Fusion- This form of fusion integrates multi-modal images originating from one or more imaging modalities to enrich image quality. Various modalities include multispectral, panchromatic, infrared, remote sensing, and visible images.

The principal advantage of fusing multiple imaging modalities lies in leveraging the complementary information present in each source image to offer a more informative depiction of the scene. This alleviates the challenges of precise diagnosis, enhances decision-making, and concurrently reduces storage costs. Conversely, image registration stands as a pivotal and demanding preprocessing task closely linked to image fusion. It rectifies spatial misalignments between input images, compensating for variations arising from translation, rotation, and scale changes [11]. It's noteworthy that image fusion can occur in either the spatial domain or the transform domain. In the spatial domain, pixel-level operations are directly applied, bypassing transform coefficients. Regions or pixels are selected based on salience metrics and are then combined using linear or nonlinear operations. Transitioning to the transform domain has motivated researchers to uncover more pronounced features that may elude capture in the spatial domain.

III. MEDICAL IMAGE FUSION

In the realm of image processing, medical image fusion pertains to the amalgamation of multiple medical images obtained from different imaging modalities or techniques, with the intent of generating a fused image that encapsulates the complementary insights from each modality [12]. The objective is to leverage the strengths of diverse imaging modalities, thereby enhancing diagnostic capabilities and fostering a more profound comprehension of medical conditions or anatomical structures. The applications of medical image fusion are manifold and encompass:

- Multi-modal Diagnosis- The fusion of images from distinct modalities such as MRI, CT, PET, or ultrasound empowers medical practitioners to attain a comprehensive overview of a patient's condition. The composite image can furnish supplementary insights about anatomical structure, functional attributes, or metabolic activity, ultimately bolstering diagnostic precision.
- Image-Guided Interventions- Image fusion proves invaluable by superimposing preoperative imaging data

onto real-time intraoperative images, facilitating surgeons in navigating and targeting with precision during minimally invasive procedures.

- Treatment Planning and Monitoring- Medical image fusion is pivotal for treatment planning and monitoring, harmonizing images taken before and after specific therapeutic interventions.
- Intensity-Based Fusion- This technique hinges on aligning and merging images based on their intensity values. Employing methods like simple averaging, weighted averaging, or maximum/minimum value selection, images are fused while preserving their original intensity characteristics.
- Feature-Based Fusion- This approach entails extracting and combining pertinent features or regions of interest from each modality. For instance, anatomical structures identified in MRI can be superimposed onto PET images, offering precise localization of metabolic activity.
- Transform-Based Fusion- Transform-based strategies, including wavelet or Fourier transforms, are harnessed to disintegrate images into frequency or spatial domains. The resultant transformed representations from distinct modalities are fused, accentuating attributes that might not be discernible in individual images.

Medical image fusion assumes a pivotal role in elevating diagnosis, treatment planning, and intervention across diverse medical domains such as oncology, neurology, cardiology, and radiology. It aids in cultivating a holistic comprehension of patient conditions, refining accuracy, and guiding efficacious medical interventions.

IV. RELATED WORK

For fusing medical images, various approaches have been explored in the literature, including feature-based or data-based fusions, as indicated in the broad classifications chart shown in figure 2. Further categories for feature-based fusion include wavelet-based, morphological operation-based and gradient-based fusion techniques. This section focuses on examining transform-based techniques such as DWT (Discrete Wavelet Transform), DCT (Discrete Cosine Transform), and NSCT (Non-Sub sampled Contourlet Transform) for fusing medical images to enhance essential aspects.

An entirely novel gradient-based algorithm for image fusion has been established by Sujoy Paul et al. [2], which utilizes the brightness and chrominance channels. The luminance channel is fused in the gradient domain. Xiangzhi Bai et al. [3] have introduced morphological operations to modify the borders between focus and defocus regions. They suggest using weighted kernels determined by the image gradient to assess the focus regions of the picture. In the work of Paresh et al. [4], wavelet-based image fusion rules using pixel-based fusions are employed.

Jayanta et al. [5] has gained popularity, where the SNR and mean square error (MSE) parameters are used to compare three different enhancement approaches. This study compares various techniques for improving color images.

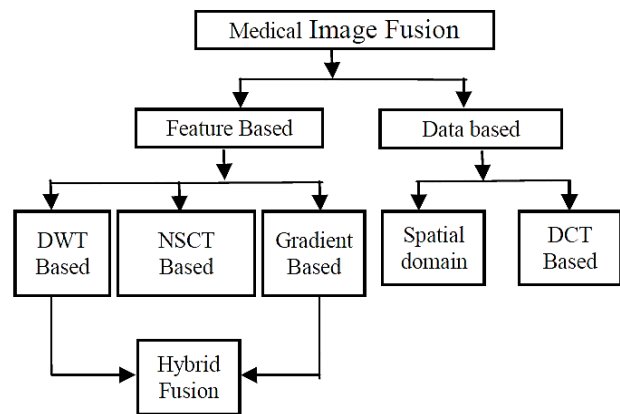


Figure 2: Classification of Medical Image Fusion methods

Sumit narayan jarholiya et al. [8] conducted research on medical images of multi-modalities captured using multiple medical camera modules. They offered two major contributions: using two levels of DWT decomposition at the front end for size reduction, and adopting the modified scaling of the DC coefficient (SDC) method for enhancing the low range of contrast of multi-modal images.

Various advanced gradient-based fusion approaches have been recently presented in the references [6], [7], and [8], respectively, for image fusion. Several fusion algorithms are used to combine multi-modality medical pictures. It has been claimed that several advanced wavelet families, including the corselet transform (CT) [9], and Xiaoxiao Li et al. [10] have proposed the Laplacian Re-decomposition (LRD) based image fusion approach for MRI and PET-based modalities using the concept of NSCT.

K. KoteswaraRao et al. [11] proposed using the energy of decomposed DWT bands to select the bands for fusing information. A spatial domain approach is utilized to further fuse the band coefficients of NSCT and DWT merged images, taking energy values into account during spatial fusion.

Discrete wavelet transform (DWT) was adopted as the most suitable wavelet transform for medical image fusion by Rajiv Singh et al. [12]. They used a simple maximum selection rule to fuse medical photos at various scales, from minimum to maximum, giving the user more freedom and flexibility in choosing the appropriate fused images. Kapinaiah et al. [13] proposed and compared various image enhancement techniques for improving the quality of MRI images. For medical MRI with PET imaging, Ehsan et al. [14] combined DWT with DCT in two phases, eventually obtaining the composite image. Initially, DCT coefficients are retrieved from input images that have been separated into 8-pixel blocks. Rakshitha.K et al. [15] conducted research analyzing various picture fusion techniques, including Principal Component Analysis (PCA), Stationary Wavelet Transform (SWT), DCT, and DWT, and conducted additional comparisons of the methods. Donia, E.A., et al. [16] compared the performance of various compressed transform-based contrast enhancement methods for low illumination images. The method mentioned that DCT transform methods can be used for improving contrast in any type of illuminations and also defined various performance measures. The DCT-based image enhancement

method is presented in [17] and [18], respectively. Various advantages and drawbacks of block-based fusion are given in [19].

V. TECHNIQUES FOR MEDICAL IMAGE FUSION

The Image Fusion technique amalgamates essential data from the provided source images, generating a composite image of superior quality compared to the input images. The strategies for image amalgamation can be categorized into two main groups:

Spatial Domain Fusion- Spatial domain operations directly manipulate the pixel values of an image to achieve the desired outcome. Fusion is applied in various contexts, including medical image analysis, microscopic imaging, satellite image analysis, remote sensing applications, computer vision, and surveillance. For instance, remote sensing images undergo analysis using customizable quality assessment tools. One prevalent method in this domain is

the distinct wavelet transform, known for its advantages in enhancing the spatial and spectral quality of the fused image when compared to other spatial techniques.

A. Transform Domain Fusion

In transform domain fusion, images are first transformed into a different domain before the fusion process takes place. The transformed domain is where the fusion is carried out, and subsequently, an inverse transformation generates the fusion output. The widely-used wavelet-based pixel-level fusion methods operate by applying wavelet transforms to extract high- and low-frequency components representing diverse perspective information within an image. Subsequently, various fusion rules are employed to combine sub-images at different frequencies.

The visual representation of the discrete transform-based fusion approach is illustrated in Figure 3.

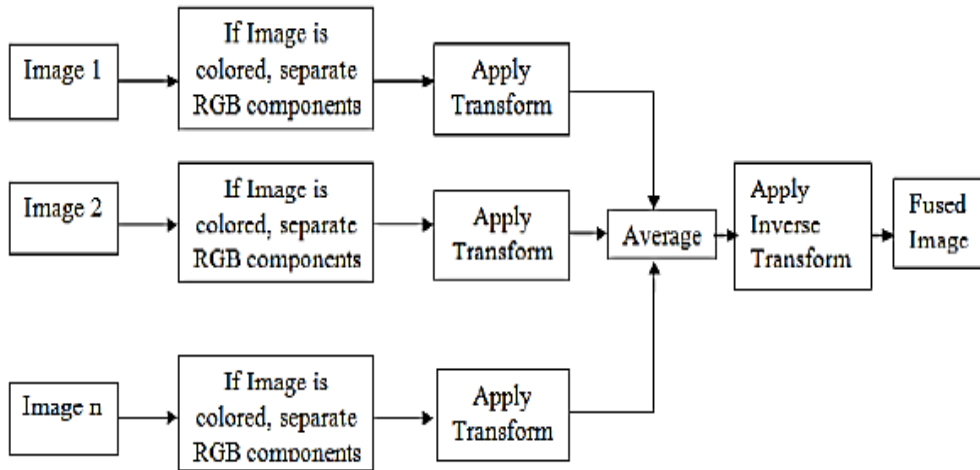


Figure 3: Discrete Transform Based Fusion

B. Principal Component Analysis (PCA)

It is a mathematical technique employed to transform interrelated variables into uncorrelated ones. Its widespread use includes image classification and data compression. The process involves a mathematical formula that generates essential components, often referred to as principal components. These components provide a concise and optimized representation of the dataset. Each subsequent component captures the remaining variance, with the initial principal component aligned with the direction of maximum variance. The second principal component is orthogonal to the first, forming a 90-degree angle. The process continues for subsequent components. PCA is particularly relevant in image fusion, where it aids in synthesizing images. As illustrated in Figure 4, PCA facilitates image fusion by combining essential components derived from input images.

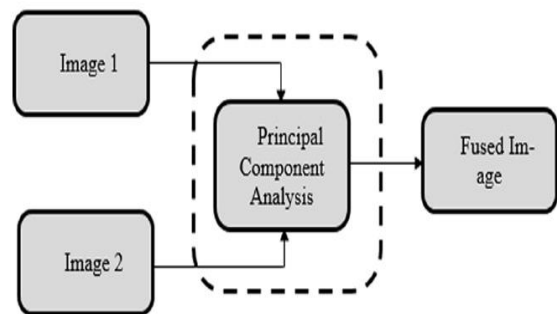


Figure 4: Image fusion using PCA

C. Discrete Cosine Transform (DCT)

It serves a significant role in image fusion, offering benefits in terms of complexity and real-time application. Many image fusion algorithms are intricate and time-intensive, posing challenges for real-time usage. Particularly when working with numbered source images and generating fused images adhering to the

JPEG standard, employing fusion techniques within the DCT domain has proven to be notably effective. To leverage JPEG compression, an initial step involves dividing an image—whether it's in color or grayscale—into 8x8 pixel blocks. The subsequent application of the Discrete Cosine Transform to each block yields a collection of 64 coefficients. These coefficients are subsequently quantized to reduce their magnitudes. Incorporating DCT-based fusion techniques has demonstrated a high level of success in generating fused images, as depicted in Figure 5. This approach provides an effective means of overcoming the complexities and time constraints associated with many image fusion methods, making it particularly suitable for real-time applications.

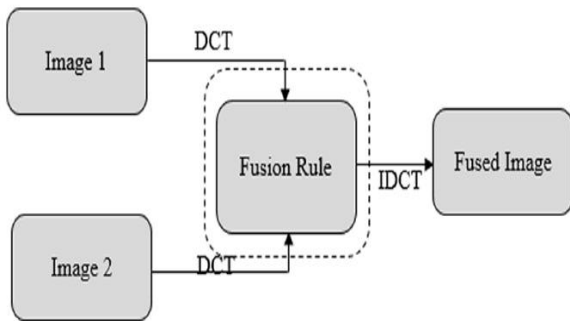


Figure 5: Image fusion by means of DCT

The Discrete Wavelet Transform (DWT) involves constructing filters specifically tailored for its decomposition process. These filters ensure that each subsequent level of the transformation chart introduces features not present in prior levels. DWT signal decomposition relies on a sequence of low-pass and high-pass filters, accompanied by a subsampling mechanism. In the context of 2D-DWT, the resulting components consist of four images, each with dimensions equivalent to half of the original image's size [22, 23]. Wavelet-based pixel-level fusion methods draw on the wavelet transform to extract high- and low-frequency components that encapsulate diverse perspective information from an image. Figure 6 illustrates a schematic depiction of a wavelet fusion algorithm that involves two registered images, $I_1(X_1, X_2)$ and $I_2(X_1, X_2)$. This approach exemplifies the fusion process within the DWT framework, showcasing the application of wavelet-based techniques to enhance image quality by combining frequency-specific sub-images.

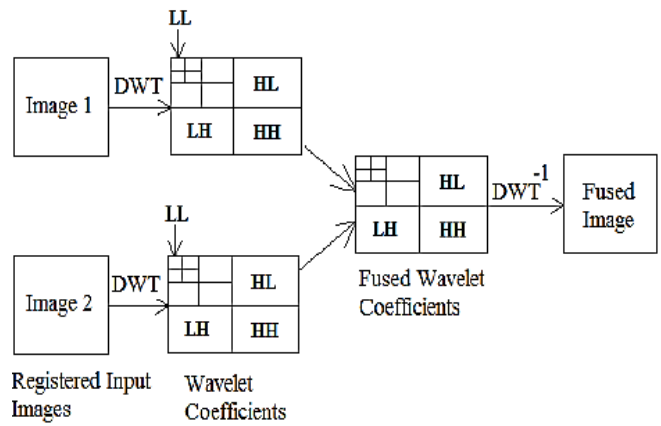


Figure 6: Block diagram of Discrete Wavelet transform

VI. MEDICAL IMAGE FUSION METHODS

The process of medical image fusion encompasses two primary stages. In classical image fusion methods, these stages involve:

- **Image Registration-** The initial stage involves image registration, which aims to correct spatial misalignments among diverse image datasets. These misalignments often require adjustments for scale changes, rotations, and translations. This registration task becomes particularly intricate when inter-image noise, missing features, and outliers are present within the images.
- **Fusion of Relevant Feature-** The second stage revolves around fusing pertinent features from the registered images. This process entails identifying and selecting features that hold significance for a specific clinical assessment goal. The selected fusion methods are then applied based on these extracted features, with applications spanning across various medical imaging studies.

Here are different methods commonly employed for medical image fusion:

- **Morphological Methods-** The concept of morphology operators, which has been extensively explored within the image processing community, has found application within the medical imaging domain for detecting spatially relevant information within medical images. These morphological filtering techniques have been utilized, for instance, in brain diagnosis. An illustration of this approach can be seen in the fusion of CT and MR images. In such scenarios, the effectiveness of morphology operators is closely tied to the structuring operator that governs opening and closing operations. A methodical sequence of these operations yields the identification of scale-specific features. These features, stemming from different modalities, serve as candidates for image fusion. It's worth noting that inaccuracies can arise when detecting features in the presence of noise and sensing errors. Fusion techniques such as averaging, morphology towers, K-L transforms, and morphology pyramids are employed to achieve data fusion. However, these methods are sensitive to the variability introduced by outliers, noise, and the size and shape of features.

- **Knowledge-Based Methods-** Within the realm of medical imaging, there exist numerous scenarios wherein the expertise of medical practitioners can be harnessed to design image segmentation, labeling, and registration techniques. Invariably, domain-specific knowledge plays a crucial role in establishing constraints for region-based segmentation. Moreover, it explicitly outlines expectations concerning the appearance of anatomical structures in a given imaging modality, especially when grouping detected regions of interest. A multitude of applications leverage domain-dependent knowledge for image fusion, encompassing tasks like segmentation, micro-calcification diagnosis, tissue classification, brain diagnosis, classifier fusion, detection of breast cancer tumors, and delineation and recognition of anatomical brain objects. In practice, knowledge-based systems can synergize with other methods, including pixel intensity. These techniques entrust a significant level of confidence in medical experts to correctly label and identify domain-specific knowledge pertinent to the fusion task.
- **Wavelet-Based Methods-** Wavelet-based image fusion relies on a fundamental concept: extracting detailed information from one image and embedding it into another. Typically, this detailed information resides in the high-frequency domain, and wavelets possess the capacity to select frequencies both in spatial and temporal dimensions. The resultant fused image inherits advantageous characteristics from both source images, enhancing the overall image quality. Various models for this information injection exist, with substitution being the simplest. More intricate mathematical models, such as simple addition operations or aggregator functions, offer alternatives. Regardless of the model employed, practical considerations dictate that image resolution remains consistent before and after fusion. Moreover, the image resolution of the reference image dictates the necessary levels of decomposition; higher-resolution images mandate more decomposition levels compared to lower-resolution counterparts.
- **Neural Network-Based Methods-** Artificial Neural Networks (ANNs) draw inspiration from biological neural networks and possess the capability to learn from inputs to process features and make comprehensive decisions. These models necessitate training on an input dataset to determine the network's parameters, referred to as weights. The inherent ability of neural network models to predict, analyze, and infer information from data, without requiring complex mathematical solutions, is viewed as an advantageous trait. This attribute makes neural networks particularly appealing for image fusion, given that the variability between images can shift whenever a new modality is introduced. Training neural networks to adapt to such variations facilitates numerous applications in medical image fusion. These applications span feature generation, classification, data fusion, image fusion, micro-calcification diagnosis, breast cancer detection, medical and cancer diagnosis, natural computing methods, and classifier fusion.
- **Methods Based on Fuzzy Logic-** The versatile properties of fuzzy logic—conjunctive, disjunctive, and

compromise—are widely explored in image processing and have demonstrated utility in image fusion. Fuzzy logic serves both as a feature transform operator and a decision operator for image fusion. This approach finds diverse applications in areas such as brain diagnosis, cancer treatment, image segmentation and integration, maximizing mutual information, deep brain stimulation, brain tumor segmentation, image retrieval, spatial weighted entropy, feature fusion, multimodal image fusion, ovarian cancer diagnosis, sensor fusion, natural computing methods, and gene expression analysis. The multifaceted nature of fuzzy logic enables its effective application across these varied domains, providing solutions for diverse challenges in image fusion tasks.

VII. CONCLUSIONS

Multimodality medical image fusion techniques are employed to integrate data from a range of images to generate a more informative composite image. This article offers a comprehensive overview of the latest trends in research within the field of multimodality medical image fusion. The analysis of existing literature reveals that numerous researchers have explored diverse fusion methods tailored for medical images. Further scrutiny of the extensive survey highlights a common challenge among these techniques, namely, the potential for adverse effects such as color distortion, compromised visual clarity, or incomplete representation of anatomical structures within the gray matter region of high-activity areas in the fused image. Additionally, these reviews underscore that many previously utilized fusion approaches suffer from spectral distortion issues and a deficiency in spatial resolution.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

- [1] Sumit Narayan Jarholiya, Dr. Shachi Awasthi., "Multimodal Medical Image Fusion Using DC Coefficient Scaling and MWGF in DWT Domain", International Journal of Research, 2021.
- [2] Sujoy Paul, Ioana S. Sevcenco and Panajotis Agathoklis. Image Fusion of multi focus and multi exposure by using Gradient Domain, University of California, 2016
- [3] Xiangzhi Bai, Miaoming Liu, Zhiguo Chen, Peng Wang, And Yu Zhang Gradient-domain Based Mathematical Morphology and Decision Map Construction for multi focus image fusion, Beijing University of Aeronautics and Astronautics, 2016.
- [4] Paresh Rawat, Jyoti Singhai, "Image enhancement method for underwater, ground and satellite images using brightness preserving histogram equalization with maximum entropy", IEEE international Conf. On Computational Intelligence and Multimedia Applications (ICCIMA) pp. 507-512. 2007.
- [5] Jayanta M., and Sanjit K. Mitra, "Enhancement of Colour Images by Scaling the DCT Coefficients", *IEEE Transactions on Image Processing*, Vol. 17, No. 10, pp. 1783-1794, 2008
- [6] F. Huang, L. Zhang, Y. Zhou and X. Gao, "Adversarial and Isotropic Gradient Augmentation for Image Retrieval with Text Feedback," in *IEEE Transactions on Multimedia*, 2022, doi: 10.1109/TMM.2022.3222624.
- [7] G. Wang, W. Li, X. Gao, B. Xiao and J. Du, "Functional and Anatomical Image Fusion Based on Gradient Enhanced

- Decomposition Model," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-14, 2022, Art no. 2508714, doi: 10.1109/TIM.2022.3170983.
- [8] H. Vargas, J. Ramirez, S. Pinilla and J. I. Martínez Torre, "Multi-Sensor Image Feature Fusion via Subspace-Based Approach Using ℓ_1 -Gradient Regularization," in IEEE Journal of Selected Topics in Signal Processing, vol. 17, no. 2, pp. 525-537, March 2023, doi: 10.1109/JSTSP.2022.3219357.
- [9] Gattim, N.K. & Rajesh, Vullanki&Partheepan, R. &Karunakaran, S. & Reddy, K.N. (2017). Multimodal image fusion using curvelet and genetic algorithm. Journal of Scientific and Industrial Research. 76. 694-696 <https://nopr.niscpr.res.in/bitstream/123456789/43038/1/JSIR%2076%2811%29%20694-696.pdf>.
- [10] Xiaoxiao Li , Xiaopeng Guo , Student Member, IEEE, Pengfei Han ,Xiang Wang , Huaguang Li , and Tao Luo , "Laplacian Redecomposition for Multimodal Medical Image Fusion" , IEEE transactions on instrumentation and measurement, vol. 69, no. 9, september 2020 /
- [11] K. Koteswara Rao, K. Veera Swam. "Multimodal Medical Image Fusion using NSCT and DWT Fusion Frame Work" International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075 (Online), Volume-9 Issue-2, December 2019 DOI: [10.35940/ijitee.B8036.129219](https://doi.org/10.35940/ijitee.B8036.129219)
- [12] Rajiv Singh and Ashish Khare. "Multiscale Medical Image Fusion in Wavelet Domain", Hindawi Publishing Corporation The Scientific World Journal Volume 2013, Article ID 521034, 10 pages <http://dx.doi.org/10.1155/2013/521034>
- [13] Kapinaiah Viswanath, Shweta , " Enhancement of Brain Tumor Images ", 2nd IEEE International Conference On Recent Trends in Electronics Information & Communication Technology (RTEICT), pp. 1894-1898, May 19-20, 2017
- [14] Ehsan Amiri, Mina Rahmanian, Saeed Amiri and Hadi Yazdani Praee, "Medical images fusion using two-stage combined model DWT and DCT", International Advanced Researches and Engineering Journal 05(03): 344-351, 2021 DOI: 10.35860/iaej.910982
- [15] Rakshitha.K, Rashmi Laxman Gavadi, Akhilraj .V. Gadagkar , "Comparison of Different Methods for Fusion of Multimodal Medical Images", International Research Journal of Engineering and Technology (IRJET) Volume: 04 Issue: 11 | Nov -2017"
- [16] Donia, E.A., El-Rabaie, ES.M., El-Samie, F.E.A. et al. Infrared image fusion for quality enhancement. J Opt 52, 658–664 (2023). <https://doi.org/10.1007/s12596-022-01018-4>
- [17] Seongbae Bang and Wonha Kim, "DCT Domain Detail Image Enhancement for More Resolved Images" ,Electronics 2021, 10, 2461. <https://doi.org/10.3390/electronics10202461>
- [18] V. Arya, H. Choubey, S. Sharma, T. -Y. Chen and C. -C. Lee, "Image Enhancement and Features Extraction of Electron Microscopic Images Using Sigmoid Function and 2D-DCT," in *IEEE Access*, vol. 10, pp. 76742-76751, 2022, doi: 10.1109/ACCESS.2022.3192416.
- [19] K. Kalaivani and Y. Asnath Vicky Phamila, "Analysis of Image Fusion Techniques based on Quality Assessment Metrics", Indian Journal of Science and Technology, Vol 9(31), DOI: 10.17485/ijst/2016/v9i31/92553, August 2016
- [20] Deron Rodrigues, Hasan Ali Virani, Shajahan Kutty. Multimodal Image Fusion Techniques based on wavelets, Goa College of Engineering, 2013.
- [21] Jarholiya, Sumit., Multimodal Medical Image Fusion Using DC Coefficient Scaling and MWGF in DWT Domain. International Journal of Research. 7. 01-11, 2021