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EFFICIENT MEDICAL IMAGE FUSION USING JOINT MULTI-RESOLUTION (DWT) AND MULTI-SCALING (DRT) TRANSFORM WITH BLOCK MATCHING

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ABSTRACT

Image Fusion is a process of combining the relevant information from a set of images into a single image, where the resultant fused image will be more informative and complete than any of the input images. Image fusion techniques can improve the quality. This paper uses MRI and CT images for fusion which contains complementary information helpful for diagnosis of disease. Proposed approach, medical image fusion based on the combined effect of Discrete Wavelet Transform (DWT) and Discrete Ripplet Transform (DRT). The images are initially transformed into multi-resolution image using DWT. The approximation image are further transformed using DRT. Then get ripplet coefficients and these are applied with Image Blocking method. The proposed method can be helpful for better medical diagnosis.

Index Terms - Image fusion, MRI Image, CT Image, Discrete Wavelet Transform (DWT), Discrete Ripplet Transform (DRT),Image Blocking.

INTRODUCTION

Image Fusion is the process of generating better quality images from two or more input images. The resultant image should retain all important features of all input images [2]. Image fusion technology can be applied to many areas dealing with images such as medical image analysis, remote sensing, military surveillance, etc [2].

The medical imaging field demands more complementary information for disease diagnosis purpose. However, this is not possible using single modality medical images as X-ray computed tomography (CT) is suited only for recognizing bone's structure, MRI giving clear information about the soft tissues and so on. In this regard, medical image fusion is the only emerging technique which has attracted researchers to assist the doctors in fusing images and retrieving relevant information from multiple modalities such as CT, MRI, FMRI, SPECT, PET [8].

Here, two input images from different image modalities are shown Fig 1 and Fig 2 .First image is a Computed Tomography (CT) image, and the second image is a Magnetic Resonance Imaging (MRI). Each image has its own limitation, which can be solved by creating the fused image from two different image modalities as shown Fig 3. This would lead to improved diagnosis, better surgical planning, more accurate radiation therapy and countless other medical benefits [2].

The main advantage of Image fusion (IF) is integrating complementary, as well as redundant information from multiple images to create a fused image for providing more complete and accurate information. Another advantage of image fusion is that it reduces the storage cost by storing only the single fused image, instead of the multisource images.

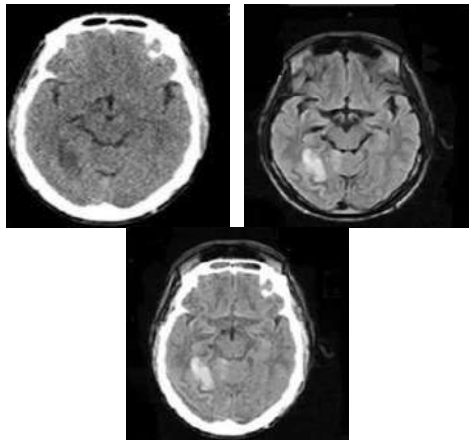

Figure 1 CT Image, MRI Image & Fused Image

Image fusion method can be broadly classified into two groups – 1.Spatial domain fusion 2.Transform domain fusion.

Spatial image fusion methods work by combining the pixel values of the two or more images to be fused in a linear or nonlinear way [6]. This simplistic approach often has serious side effects. Pixel level image fusion methods are affected by blurring effect which directly effect on the contrast of the image [6]. The limitations of Spatial Domain are resolved by Transform Domain.

In Transform Domain, Image is first transferred into frequency domain. The input images are decomposed based on transform coefficients. Then the fusion technique is applied, and the fusion decision map is obtained. Then after inverse transform on that decision map produce fused image. Wavelet Transform is a faster developed multi-resolution analysis image fusion method. The problem with Wavelet Transform (WT) is that it can preserve spectral information efficiently but cannot express spatial characteristics well [7]. So, Recently, a theory called Multi-scale Geometric Analysis has been developed. Many MGA tools were proposed, such as Curvelet, Contourlet, Ripplet etc. Which have higher directional sensitivity [1].

In this paper , Medical Image fusion is based on combining multi-resolution transform (DWT) and multi-scaling transform (DRT). It use the Image Blocking method.

RELATED WORKS

The literature study delves into various techniques and algorithms related to multimodal medical image fusion, encompassing a range of approaches aimed at enhancing image quality, information content, and applicability in diverse domains.

Kesharwani et al. [1] propose a hybrid multimodal medical image fusion method combining MWGF with DC coefficient scaling and pixel-level wavelet fusion. Awang et al. [2] focus on the design and optimization of a homomorphic medical image fusion algorithm. Vanitha et al. [3] introduce a multimodal medical image fusion approach based on hybrid L1-L0 layer decomposition.

A survey conducted by Dolly and N. A.K. [4] provides an overview of different multimodal medical image fusion techniques and methods, offering valuable insights into the current landscape of image fusion technologies.

Yang et al. [5] present a multimodal medical image fusion technique based on fuzzy discrimination with structural patch decomposition, emphasizing the importance of incorporating fuzzy logic in image fusion processes. Nair and Singh [6] explore multi-sensor, multi-modal medical image fusion for color images using a multi-resolution approach, showcasing the versatility of fusion techniques across different image types.

Abdulkareem [7] focuses on the design and development of multimodal medical image fusion using discrete wavelet transform, highlighting the significance of wavelet-based approaches in image fusion.

Guo et al. [8] delve into medical image segmentation based on multi-modal convolutional neural networks, with a particular emphasis on image fusion schemes. Talbi and Kholladi [9] introduce a fusion approach using predator-prey optimization and DTCWT, showcasing innovative methods of combining optimization techniques with wavelet transforms for enhanced fusion outcomes.

Biswas et al. [10] propose spine medical image fusion using a Wiener filter in the shearlet domain, demonstrating the efficacy of domain-specific filters in improving fusion results. Lan et al. [11] explore multimodal medical image fusion using wavelet transform and the human vision system, leveraging insights from human perception to enhance fusion outcomes.

Yang et al. [12] present a medical image fusion method based on lifting wavelet transform and dual-channel PCNN, showcasing the integration of neural network models with wavelet transforms for improved fusion performance.

Yang and Liu [13] focus on the research and development of medical image fusion, providing a comprehensive overview of fusion techniques and their applications. Bazavan and Grososiu [14] introduce a hybrid fusion process with a percentage of involvement of transformation criteria, highlighting the importance of considering multiple criteria in fusion algorithms.

Tao and Qian [15] propose an improved medical image fusion algorithm based on wavelet transform, emphasizing the role of advanced signal processing techniques in enhancing fusion outcomes.

Collectively, these studies contribute to the rich landscape of multimodal medical image fusion, offering diverse perspectives and innovative approaches to address the challenges and opportunities in this field.

DISCRETE WAVELET TRANSFORM (DWT)

Discrete Wavelet Transform provides directional information in decomposition levels and contain unique information at different resolutions [1]. The fusion procedure based on wavelet transform can be described as follows.

1. The images to be fused must be registered to assure the corresponding pixels are aligned [3].
2. These images are decomposed into wavelet transformed images respectively, based on wavelet transformation. The transformed images include one low frequency portion (low-low band) and three high frequency portions (low-high bands, high-low bands, and high-high bands) [3].
3. The transform coefficients of different portions or bands are performed with some fusion rules [3].
4. The fused image is constructed by performing an inverse

wavelet transform based on the combined transform coefficients from step 3 [3].

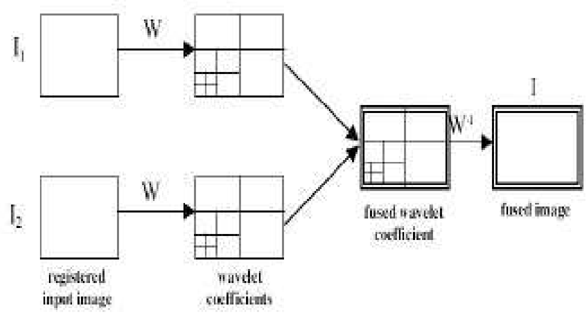

Figure 2 Block Diagram of DWT based Image Fusion[3]

DISCRETE RIPPLET TRANSFORM (DRT)

The Discrete Ripplelet Transform (DRT) is a relatively recent addition to the field of signal processing, specifically in the domain of image and signal analysis. It belongs to the broader family of wavelet transforms and shares many characteristics with the Discrete Wavelet Transform (DWT). However, it distinguishes itself through its unique handling of wavelet coefficients, leading to potential advantages in certain applications.

Basic Principles: The DRT, like other wavelet transforms, operates by decomposing a signal or image into different frequency components at multiple scales. It uses a set of basis functions known as ripplelets, which are oscillatory waveforms with ripples that propagate along their length. These ripplelets capture both local and global features of the signal or image, making them suitable for various analysis tasks.

Advantages:

Directionality: One of the key advantages of DRT is its directional sensitivity. Unlike traditional wavelets that are isotropic (directionally invariant), ripplelets can capture directional information more effectively.

Edge Detection: The directional sensitivity of ripplelets makes them particularly useful for edge detection and feature extraction in images.

Sparse Representation: DRT often leads to a sparse representation of signals or images, which can be advantageous for compression and denoising applications.

Feature Preservation: In image processing tasks such as fusion, registration, and enhancement, DRT can preserve important features while reducing noise and artifacts.

Applications:

Medical Imaging: DRT has found applications in medical image analysis, including MRI and CT image processing, where preserving fine details and edges is crucial.

Remote Sensing: In remote sensing applications, DRT's ability to capture directional information makes it valuable for analyzing satellite imagery, especially for tasks like land cover classification and change detection.

Biometrics: DRT has also been explored in biometric systems for features like fingerprint recognition and face detection, where capturing unique and discriminative features is essential.

Challenges:

Computational Complexity: Like other transform methods, DRT can be computationally intensive, especially for large-scale data processing.

Parameter Selection: Choosing appropriate parameters such as the scale and direction of ripplelets can significantly impact the results, requiring careful tuning in practical applications.

Integration with Other Techniques: Integrating DRT with other processing techniques, such as deep learning algorithms, may pose challenges due to differences in representation and optimization.

Overall, the Discrete Ripplelet Transform offers a promising alternative or complement to traditional wavelet transforms, particularly in applications where directional information and feature preservation are paramount. Ongoing research continues to explore its capabilities, optimizations, and integration with modern signal and image processing techniques.

PROPOSED MEDICAL IMAGE FUSION ALGORITHM

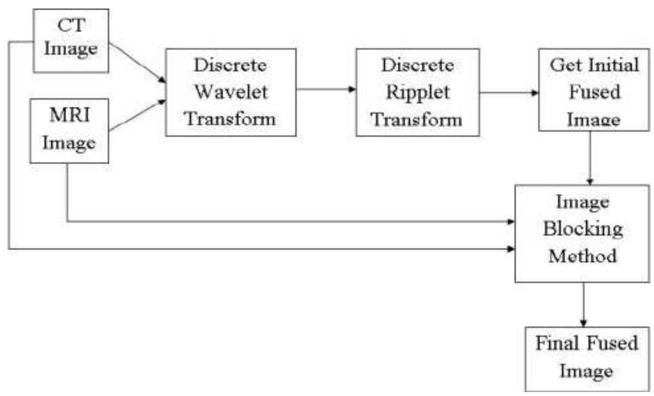

Figure 3 Block Diagram of proposed Image Fusion Method

Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are two widely used imaging modalities in the medical field, each with its strengths and limitations. Fusion of MRI and CT images can provide a comprehensive view by combining the structural information from CT with the soft tissue contrast of MRI. Here's how you can approach MRI-CT fusion using a combination of Discrete Wavelet Transform (DWT) and Discrete Ripplelet Transform (DRT):

Preprocessing:

Image Registration: Align the MRI and CT images spatially to ensure that corresponding anatomical structures are in the same coordinate system.

Intensity Normalization: Adjust the intensity values of the images to ensure consistent brightness and contrast across modalities.

Decomposition:

DWT Decomposition (for MRI): Apply DWT to the MRI image to obtain coefficients at different scales and orientations. This decomposition helps capture both global and local features.

DRT Decomposition (for CT): Similarly, use DRT on the CT image to extract directional information and edge features, which are crucial for structural details.

Feature Extraction:

Select Relevant Coefficients: Choose the DWT and DRT coefficients that represent the most significant features in each modality. This selection can be based on magnitude, entropy, or other relevant criteria.

Combine Coefficients: Combine the selected coefficients from both transformations into a single feature vector for each pixel or region of interest.

Fusion Strategy:

Transform Domain Fusion: Apply a fusion strategy in the combined feature domain. This can include techniques such as weighted averaging, maximum selection, or rule-based fusion.

Adaptive Fusion: Consider adaptive fusion methods that adjust the fusion process based on local image characteristics, ensuring optimal preservation of details and structures.

Inverse Transform:
Inverse DWT and DRT: Perform the inverse transforms using the fused feature vector to reconstruct the fused image.

Post-processing: Apply any necessary post-processing techniques such as noise reduction or contrast enhancement to improve the visual quality of the fused MRI-CT image.

Evaluation:
Quantitative Metrics: Evaluate the fused image using quantitative metrics such as Structural Similarity Index (SSI), Peak Signal-to-Noise Ratio (PSNR), or Mutual Information (MI) to assess the quality of fusion compared to the original images.

Visual Inspection: Conduct a visual inspection by radiologists or experts to ensure that important structures and details are preserved in the fused image.

By combining the strengths of DWT and DRT in MRI-CT fusion, you can achieve a fused image that retains both the structural information from CT and the soft tissue contrast from MRI, aiding in more accurate diagnosis and treatment planning in medical imaging applications.

And finally get fused Image.

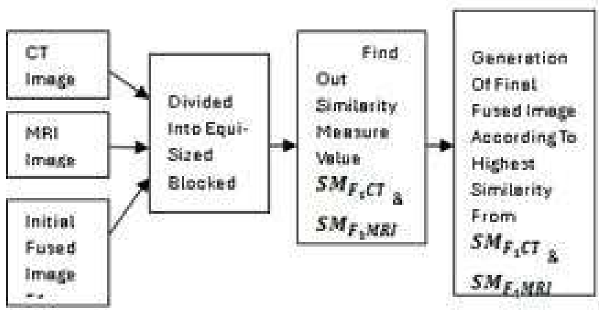

Figure 4 Block Diagram of Image Blocking Method

RESULTS ANALYSIS

Entropy:
Entropy is a key quantitative measure in image fusion, assessing the information content of the fused image. It considers the probability distribution of gray levels in the image, reflecting the randomness or uncertainty present. Higher entropy indicates a more diverse range of gray levels and potentially richer information in the fused image.

Peak Signal-to-Noise Ratio (PSNR):
PSNR is a commonly used metric to evaluate the quality of image fusion. It compares the maximum possible power of a signal with the power of noise that affects its fidelity. A higher PSNR value signifies better fusion results with less distortion or loss of information.

Normalized Cross Correlation (NCC):
NCC is utilized to measure the similarity between the fused image and a reference image, often one of the source images used in fusion. It quantifies how well the fused image aligns with the original data, with higher NCC values indicating a closer resemblance and better alignment between the images.

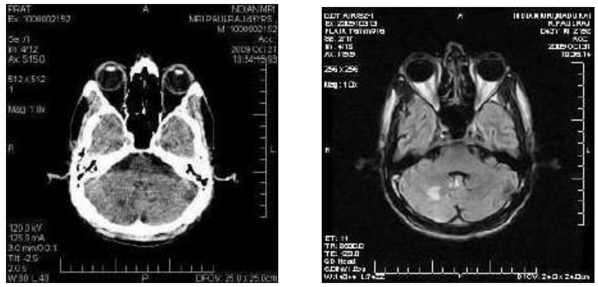

Figure 5 CT Image & MRI Image

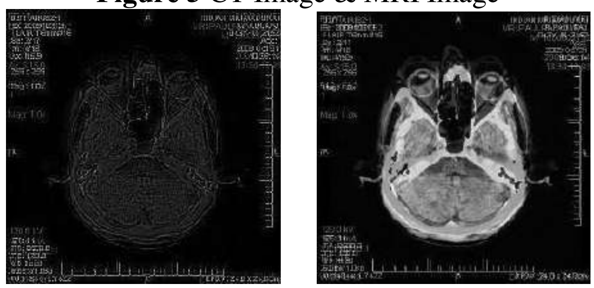

Figure 6 DWT & DRT Fused Image

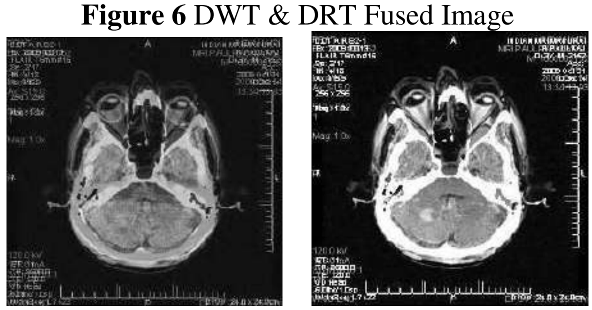

Figure 7 CT Image & MRI ImagE Final Combine Fusion & With Blocking Method

Table I Results Analysis

Techniques	**Dataset1**		**Dataset2**	
	PSNR	**Entropy**	**PSNR**	**Entropy**
DWT	18.0981	1.2303	18.2714	0.5267
DRT	27.9235	5.6535	24.1742	5.9139
DWT+DRT	23.6363	5.9625	23.7549	6.0842
DWT+ DRT+ Image Blocking Method	65.6083	6.0551	61.4775	6.2839

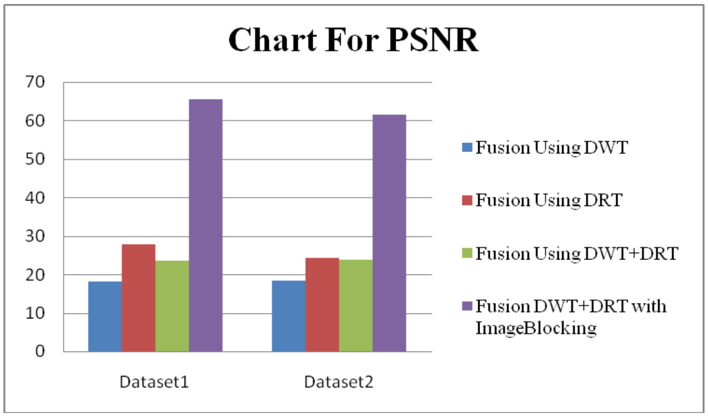

Figure 8 Psnr Graph

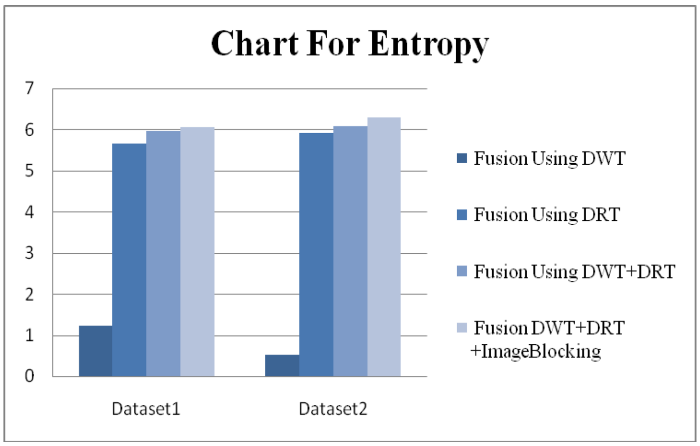

Figure 9 Entropy Graph

CONCLUSION

The proposed image fusion method based on combination of Discrete Wavelet Transform and Discrete Rippled Transform worked efficiently for fusion of medical imaging applications. The Quality and Quantity of Fused Image measured based on the PSNR value, Entropy. PSNR value must be increase, the higher the value of the PSNR means the better fusion result. Here by it is concluded that the proposed image fusion method based on combination of Discrete Wavelet Transform and Discrete Ripplet Transform with blocking image method works efficiently for fusion of medical imaging applications. DWT give unique information at different resolutions. DRT is designed to represent images at different scales and different directions. Applying Image Blocking method, each block of fused image is original block of any of the input image and improved the visual quality of input images.

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