CT , MRI & PET Image Fusion Using 3-D Discrete Shearlet Transform and ROI Localization

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ABSTRACT

MRI, CT, and PET are examples of medical imaging technologies that offer further diagnostic data. High soft tissue contrast is provided by MRI, precise bone structures are captured by CT, and metabolic and functional activity is highlighted by PET. Accurate clinical interpretation may be limited, nevertheless, if these modalities are examined separately. By combining many modalities into a single composite image, image fusion techniques seek to increase both structural and functional features for better diagnosis and treatment planning.

A 3D-DST based fusion framework for merging MRI, CT, and PET images is proposed in this research. The shearlet transform is ideally suited for representing medical images because it is especially good at capturing anisotropic features like edges, textures, and directional details. The suggested method uses 3D-DST to break down source images into low- and high-frequency sub-bands. Then, an appropriate fusion procedure is used: high-frequency coefficients are fused using a maximum-absolute or energy-based selection technique to preserve structural and functional details, while low-frequency coefficients are fused using weighted averaging to maintain overall intensity. In the end, inverse 3D-DST is employed to reconstruct the merged image.

Comparing the suggested approach to traditional transform-based fusion techniques like wavelet and contourlet transforms, experimental tests on multimodal medical datasets show that it performs better in terms of information preservation, edge clarity, and diagnostic visibility. According to the findings, 3D-DST based fusion effectively combines complementary anatomical and functional data, providing radiologists with a more thorough perspective for clinical decision-making in follow-up analysis, treatment planning, and disease identification.

Keyword : MRI (Magnetic Resonance Imaging) , CT (Computed Tomography) , PET (Positron Emission Tomography), Shearlet Transform (ST) , 3-D Discrete Shearlet Transform (3D-DST).

1. INTRODUCTION

Clinical diagnosis, surgical planning, and disease monitoring all heavily rely on medical imaging. A variety of imaging techniques, including MRI, CT, and PET, offer complimentary insights into the anatomical and functional properties of human tissues. PET provides information on metabolic and functional activity, CT provides great visualization of bone and dense structures, and MRI offers high soft-tissue contrast and structural detail. On the other hand, depending only on one modality frequently results in unclear or insufficient interpretation. In order to get over this restriction, medical image fusion techniques are used to combine the advantages of several modalities into a single composite image that improves clinical judgment.

The use of transform-domain techniques for medical picture fusion has grown significantly in recent years. When it comes to capturing multidirectional and anisotropic aspects of medical pictures, conventional techniques like wavelets and contourlets are limited. The Shearlet Transform (ST), which effectively depicts edges, directional details, and geometric structures, was developed in response to this issue. Shearlets, as opposed to wavelets, offer multiscale and multidirectional analysis, which makes them ideal for complex medical data.

By combining spatial, structural, and directional information at the same time, the 3-D Discrete Shearlet Transform (3D-DST) effectively represents volumetric medical data in three dimensions. Fusion rules can be used to extract important information from each modality by breaking down MRI, CT, and PET volumes into shearlet coefficients. This is followed by the reconstruction of a single augmented image. For radiologists and doctors, this merged image improves visualization by offering both functional and anatomical accuracy.

The 3-D Discrete Shearlet Transform provides a sophisticated framework for combining multimodal medical data, including MRI, CT, and PET image fusion. Compared to traditional fusion techniques, the method adds fine details, maintains structural edges, and produces a more informative representation. In fields like neurology, oncology, and others where precise diagnosis necessitates immediate access to anatomical and functional data, this makes it very useful.

1.1 Objectives

- Create a multiscale, multi-orientation fusion of CT, MRI, and PET volumes using 3D-DST.
- Create ROI-adaptive fusion weights by localizing ROIs (organs or lesions).
- Assure artifact suppression and structural coherence.
- Validate quantitatively using clinical cases and publicly available 3-D datasets.

2 LITERATURE SURVEY

Clinical applications and translational research in medical imaging are finding that imaging data fusion is becoming a barrier. The objective of this research is to apply a new multimodality medical image fusion method to the field of shearlets. The suggested technique extracts both low- and high-frequency picture components using the non-subsampled shearlet transform (NSST). A clustered dictionary learning strategy based on modified sum-modified Laplacian (MSML) is offered as a novel method for fusing low-frequency components. High-frequency coefficients can be fused in the NSST domain using directed contrast. The inverse NSST approach is used to create a multimodal medical image [1].

Accurately identifying diseases and developing better treatments are the two biggest challenges facing medicine. Clinical staff find it difficult to diagnose diseases with a single imaging modality. A new structural and spectral feature improvement technique for multimodal medical image fusion (MMIF) in the NSST domain is presented in this research. The suggested approach first creates two image pairings using the Intensity, Hue, Saturation (IHS) method. Low frequency and high frequency sub-bands are then obtained by decomposing the input images using the Non-Subsampled Shearlet Transform (NSST) method. Next, Low Frequency Sub-bands (LFSs) are fused using a suggested Structural Information (SI) fusion technique. It will improve the information about the structure (texture, backdrop) [2].

Multimodal medical imaging is a useful tool for addressing a number of clinical issues, including postoperative care and clinical diagnosis. This paper proposes a convolutional sparse representation (CSR) and mutual information correlation-based medical picture fusion technique. This technique uses a non-subsampled shearlet transform to break down the source image into a single high-frequency and a single low-frequency sub-band. CSR is utilized for high-frequency coefficient fusion in the high-frequency sub-band. By using mutual information correlation analysis, several fusion procedures are applied for various parts of the low-frequency sub-band. The performance of this approach is robust in terms of five standard objective measures, according to an analysis of two types of medical image fusion challenges, namely CT–MRI and MRI–SPECT. The experimental results demonstrate that the suggested method outperforms the other six sophisticated medical picture fusion techniques in terms of subjective vision and objective evaluation criteria [3].

This research proposes a multi-modal medical image fusion approach based on nonsubsampled contourlet transform (NSCT) and pulse coupled neural networks (PCNN) techniques. The input images are divided into high- and low-frequency subbands using the NSCT technique. The PCNN is a fusion rule for merging low- and high-frequency subbands. Reconstructing the fused image is the opposite of the NSCT procedure. Medical picture fusion results assist physicians in diagnosing illnesses and treating patients. Eight fusion techniques are contrasted with the suggested algorithm [4].

In order to dynamically extract efficient and thorough information from the corresponding modalities, this study suggests a dynamic image fusion framework called MoE-Fusion, which uses a multi-modal gated mixture of local-to-global experts. Under the direction of a multi-modal gate, our model comprises a Mixture of Local Experts (MoLE) and a Mixture of Global Experts (MoGE). The MoLE performs specialized learning of multi-modal local features, which causes the fused images to retain the local information in a sample-adaptive manner, whereas the MoGE focuses on the global information that improves the fused image with overall texture detail and contrast. Several experiments show that our MoE-Fusion outperforms state-of-the-art methods in preserving multi-modal image texture and contrast utilizing the local-to-global dynamic learning paradigm, and it also performs better on detection tasks [5].

3. PROPOSED METHODOLOGY

Anisotropic properties in multivariate problem classes can be effectively encoded using shearlets, a multidirectional and multiscale framework. Shearlets were first presented in 2006 for both sparse approximation and function analysis. Wavelets naturally extend into shearlet transformations. Shearlets take into account the fact that anisotropic characteristics, such edges in images, usually regulate multivariate functions. However, such behaviors cannot be captured by wavelets, which are isotropic objects. A few generating functions are subjected to parabolic scaling, shearing, and translation to produce shearlets. The number of orientations doubles at each scale in the shearlet tight frame structure. The parabolic scaling law, which states that length² ≈ width, effectively supports shearlets at the tiny scales within narrow, directed ridges. The affine group gives birth to shearlets, which enable a cohesive handling of the digital and continuum scenarios, resulting in faithful implementations.

There are four steps in the shearlet transform-based medical picture fusion process. These include picture preprocessing, image reconstruction, decomposition, and fusion rules.

Step1 : Pre-processing

In order to preprocess an image, undesirable distortions are suppressed or features that are needed for additional processing are enhanced.

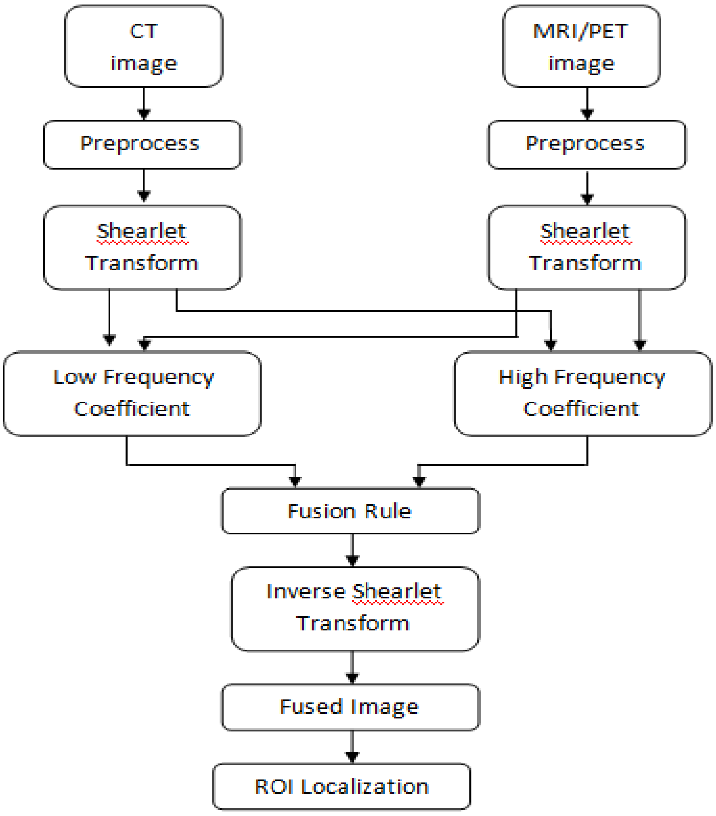


Figure 1 Flowchart for Image Fusion based on Shearlet Transform

Step2 : Decomposition

Here, the shearlet transform is used to decompose images A (CT) and B (MRI), respectively, and determine the appropriate shearlet coefficients. Both vertical and horizontal cones are used in this technique. Each image's decomposition is divided into two sections: the J-level multi-scale wavelet packets and the multi-direction (Kth directions) decomposition.

Step3 : Fusion Rule

The human feature visibility fusion approach is used to select shearlet low frequency coefficients. The idea of human feature visibility is presented as a way to assess an image's quality. Better details and conformity to the human observer are made possible by the human visual feature.

Step4 : Reconstruction

The fused image is obtained by reconstructing the updated fused coefficients using the inverse shearlet transform.

4. IMPLEMENTATION

First the images are pre-processed to remove noise and to clean the images using imgaussfilt function , imgaussfilt is used when you want to smooth an image, remove noise, or prepare it for edge detection.

After that images are transformed using 3D shearlet and fused after fusion inverse shearlet transform is applied. Image processing is applied to localise ROI.

Following sections shows the various combination of MRI , CT and PET for fusion.

4.1 CT-MRI Fusion

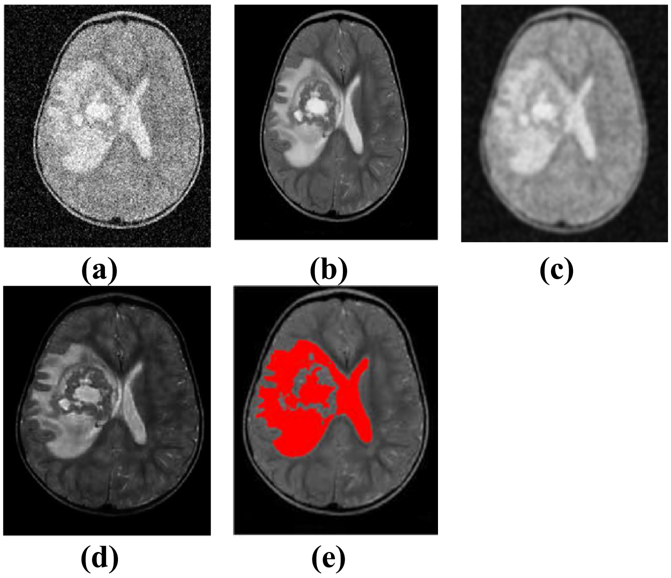
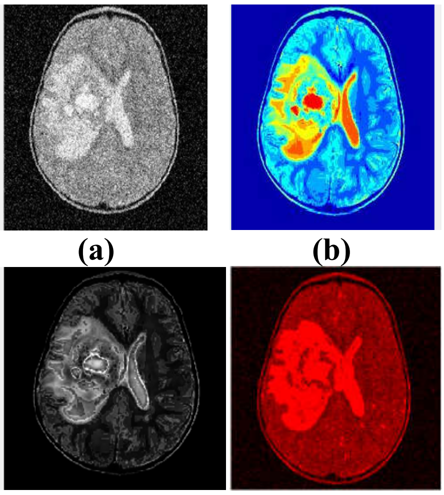


Figure 2 (a)CT image (b) MRI Image (c) After pre-processing (d)Fused Image (e) ROI Localization

In figure 2 the fusion process of CT and MRI is shown , figure (c) shows pre-processed image , figure (d) shows fused image and figure (e) shows the ROI localization.

4.2 CT – PET Fusion

CT and PET fusion process is shown in figure 3 , (a) (b) shows input images (c) shows fused image and figure (d) shows localization of ROI.

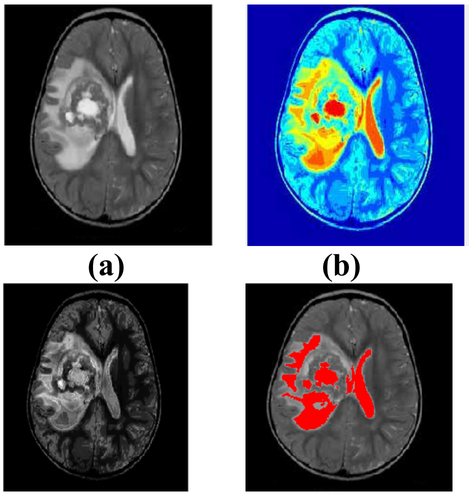


(a) (b)

(c) (d)

Figure 3 (a) CT image (b) PET Image (c) Fused Image (d) ROI Localization

4.3 MRI – PET Fusion



(a) (b)

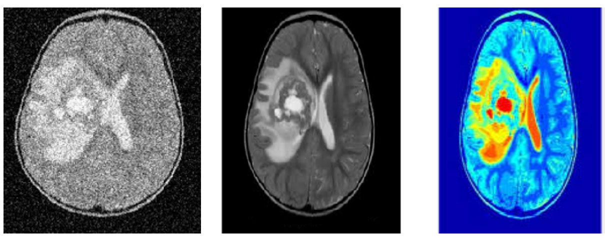
(c) (d)

Figure 4 (a) MRI image (b) PET Image (c) Fused Image (d) ROI Localization

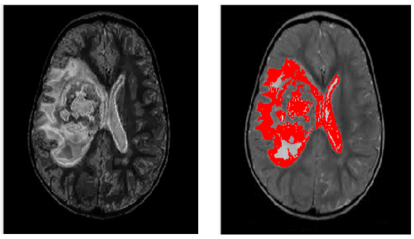
Figure 4 showing MRI and PET fusion process (a) (b) shows input images (c) shows fused image and figure (d) shows localization of ROI.

4.4 CT - MRI - PET Fusion

All Three type of images fusion is carried out and the results are shown as figure 5, Figure (a) (b) and shows CT , MRI and PET input images respectively , figure (d) showing the Fused image of all three and (e) shows the localisation of ROI.



(a) (b) (c)



(d) **(e)**

Figure 5 (a) CT image (c) MRI Image (c) PET Image (d) Fused Image (e) ROI Localization

5. RESULT & ANALYSIS

Following four metrics are used for performance analysis between the original images and fused image :

a. Mutual Information (MI) is a similarity measure used to quantify the relationship between two images. Higher MI is the better.

b. Structural Similarity (SSIM) : value typically ranges from 0 to 1, where 1 indicates perfect similarity between two images and values closer to 0 indicate lower similarity. Higher is the better.

c. PSNR (Peak Signal-to-Noise Ratio): It measures the proportion between the original signal's maximum power and the strength of any noise or distortion added during processing. Better image quality is indicated by a higher PSNR value.

d. Entropy : a statistical indicator of its information content that shows how uncertain or random the pixel values are. A low entropy image is uniform and straightforward, whereas a high entropy image appears complex due to its wide range of pixel values. Therefore, greater entropy is preferable.

	CT MRI	CT PET	MRI PET	CT MRI PET
MI	1.93	1.46	1.92	1.89
Entropy	7.06	6.89	6.98	7.05
PSNR	20.35	10.72	18.03	19.30
SSIM	0.86	0.11	0.72	0.74

Table 1 : Comparison of performance metrics between various combinations.

According to Table 1 , it is clear that the CT+MRI fusion is best amount all combinations.

Table 2 shows the entropy comparison between individual images and the fused combination.

CT	MRI	PET	Fused
6.60	4.87	-----	7.06
6.60	-----	5.08	6.89
-----	4.87	5.08	6.98
6.60	4.87	5.08	7.05

Table 2 : Entropy comparison

Figure 6 shows the MI Comparison of existing and various combination using proposed method., graph shows that CT+MRI combination is better

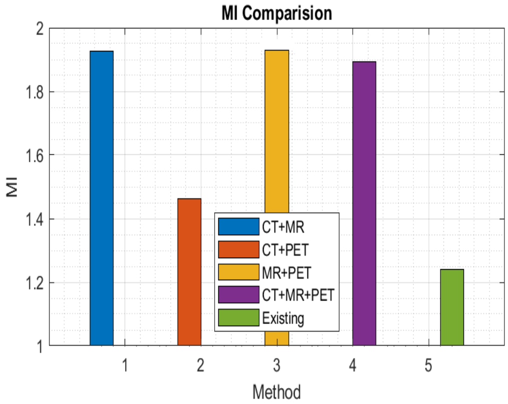


Figure 6 : MI Comparison

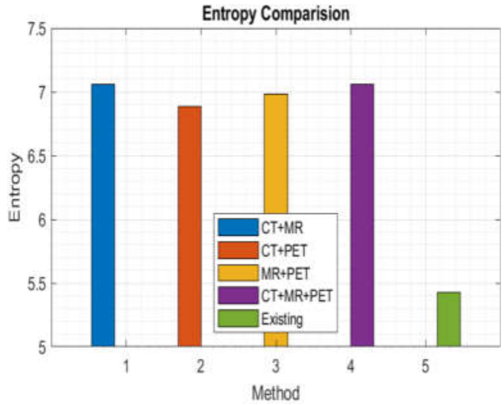


Figure 7 : Entropy Comparison

Figure 7 shows the Entropy Comparison of existing and various combination using proposed method., graph shows that CT+MRI combination is better

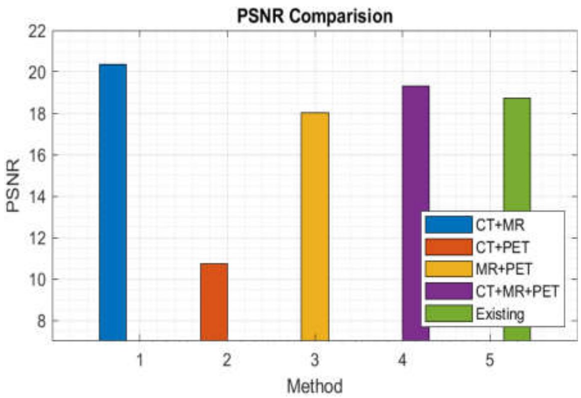


Figure 8: PSNR Comparison

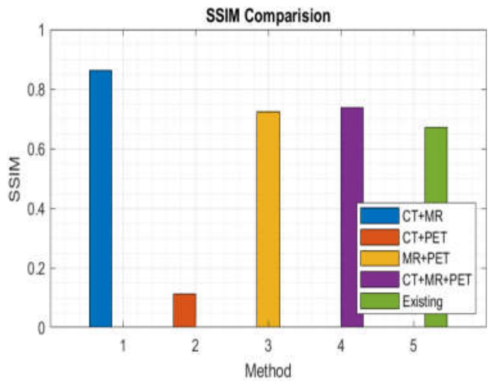


Figure 9: SSIM Comparison

In Figure 8 the PSNR Comparison shows CT+MRI combination is better , In Figure 9 the SSIM Comparison shows CT+MRI combination is better.

6. CONCLUSION

Better visual outcomes, such as sharpness and smoothness, are obtained in high-textured photos using the suggested strategy. In addition to the visual results, performance measures are also assessed, and their values indicate superior outcomes when compared to current techniques. The paper talks about a variety of imaging data mistakes. Additionally, it contrasts the data gathered for computation from the original image and displays the information's improvement and lack of noise in the fused image. According to the results, the results of the current transform domain methods are superior to those of alternative existing methods. In addition to visual effects, the performance measurements show that transform domain methods outperform similar spatial domain schemes.

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