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Comparative Analysis of DCT, DWT& CNN Based Medical Image Fusion For PET-MRI

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ABSTRACT

Medical image fusion is the process of integrating complimentary information from many imaging modalities, and it significantly increases the accuracy of diagnosis. In this research, we develop a fusion approach based on the discrete wavelet transform (DWT) for PET-MRI image integration using MATLAB. Both PET and MRI images must be frequency subband decomposed before an energy-based fusion rule is applied and the fused image is reconstructed using the inverse discrete wavelet transform. The proposed technique preserves the spatial information gained from MRI while maintaining the functional insights gained from PET. Performance is evaluated using metrics like Mutual Information (MI), the Peak Signal-to-Noise Ratio (PSNR), and the Structural Similarity Index (SSIM). The tests' comparative results demonstrate that DWT-based fusion outperforms conventional fusion techniques in terms of effectively enhancing contrast and structural integrity. Clinical decision-making is aided by the enhanced visibility of lesions due to the combined images. The findings of this research show that wavelet-based fusion may prove to be a computationally efficient approach for applications involving multimodal medical imaging. Future work will use deep learning enhancements to further automate procedures.

Keywords: *Medical Image Fusion, Discrete Wavelet Transform (DWT), PET-MRI Integration, Multimodal Imaging, Wavelet-Based Fusion, MATLAB Implementation, Diagnostic Enhancement.*

1. INTRODUCTION

Since medical imaging provides non-invasive methods for disease monitoring and diagnosis, it is crucial to modern healthcare. Although every imaging technique has advantages of its own, no single modality can provide all the diagnostic information needed. Positron Emission Tomography (PET) captures functional metabolic activity, whereas Magnetic Resonance Imaging (MRI) provides high-resolution structural features. However, isolated PET images have inadequate spatial resolution, and MRI does not provide functional insights [1]. To overcome these limitations, medical image fusion techniques are used to merge complementing data from both modalities into a single, enhanced image. Discrete Wavelet Transform (DWT)-based fusion has gained popularity among fusion systems because to its ability to efficiently integrate features by breaking down images into multi-resolution frequency subbands.

DWT-based medical picture fusion splits input images into detail and approximation coefficients using wavelet transforms. This deconstruction enables better extraction of structural and functional information. The low-frequency (approximation) subbands preserve the general image structure, while the high-frequency (detail) subbands capture edges and fine details. The fused image is improved by applying the appropriate fusion criteria, such as maximum selection, averaging, or weighted averaging, which preserve the most relevant information from PET and MRI images. After fusion, a Inverse DWT (IDWT) is used to rebuild the final output [2]. Compared to traditional pixel-based or basic arithmetic fusion methods, DWT-based fusion enhances image contrast, removes redundant information, and preserves significant diagnostic features.

The primary objective of this research is to implement and evaluate DWT-based fusion for PET-MRI images using MATLAB. MATLAB provides a robust computational environment for image processing with integrated wavelet decomposition and reconstruction tools. The technique uses image pre-processing, wavelet decomposition, coefficient fusing, and inverse transformation to produce a high-quality fused image. In order to assess performance, quantitative metrics such as Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Mutual Information (MI) are employed to compare the fused image with the original inputs. These metrics provide insight into how well visual quality and diagnostic accuracy are maintained during the fusion process.

Several studies have looked into different fusing techniques, including Principal Component Analysis (PCA), Intensity-Hue-Saturation (IHS) transformation, and CNN fusion based on deep learning. Despite their promising results, deep learning techniques require large datasets and a lot of processing capacity [3]. However, because it strikes a compromise between accuracy and efficiency, DWT-based fusion is a good choice for real-time medical applications. Furthermore, wavelet-based techniques effectively suppress noise, improve edge preservation, and limit information loss, making them particularly well-suited for multimodal medical picture fusion.

This research is important because it has the potential to improve clinical decision-making. By providing radiologists with a more informative fused image, the suggested approach can aid in early illness identification, treatment planning, and patient monitoring [4]. PET-MRI fusion is particularly useful in oncology, neurology, and cardiology, where accurate imaging is crucial for disease characterization. Future studies could look into hybrid approaches, including DWT coupled with deep learning, to further enhance the fusion process [5].

This research concludes by demonstrating how well DWT-based PET-MRI fusion using MATLAB integrates multimodal data. The proposed method is a valuable tool for medical picture analysis since it enhances structural and functional information.

2. RELATED WORKS

In the well-researched topic of medical image fusion, several strategies have been proposed in recent years to improve diagnostic imaging. Several studies have examined transform-based approaches, such as Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), and Stationary Wavelet Transform (SWT), in addition to deep learning-based techniques for multimodal image fusion [6]. Depending on the imaging modalities and the amount of information retention required, each strategy offers pros and cons.

One well-liked fusion method that researchers have looked into for merging PET and MRI images is Principal Component Analysis (PCA). PCA reduces the dimensionality of images by reducing redundancy and extracting key components. However, studies have shown that PCA-based fusion typically loses fine structural information, which makes it inappropriate for high-precision medical applications. Intensity-Hue-Saturation (IHS) transformation has also been employed to enhance contrast in multimodal image fusion; nevertheless, it struggles to comprehend complex medical picture textures [7].

A widely used tool, the Discrete Wavelet Transform (DWT) is renowned for its multi-resolution representation capability. DWT-based fusion successfully combines functional and anatomical data while preserving spatial resolution, as demonstrated by Li et al. (2020). After comparing DWT, Stationary Wavelet Transform (SWT), and Contourlet Transform (CT), they discovered that DWT offers a better trade-off between computational efficiency and image quality. In another work by Zhang et al. (2021), energy-based selection criteria improved the retention of critical diagnostic information in DWT-based image fusion using adaptive fusion rules [8].

Several researchers have extended its application by integrating DWT fusion with Pulse Coupled Neural Networks (PCNNs).Guo et al. (2019) presented a PCNN-DWT-based hybrid model that enhances contrast and edge retention. Their testing data showed that the hybrid approach performed better than traditional DWT fusion in medical imaging applications. However, the growing processing complexity limits its real-time applicability [9].

In recent years, deep learning-based image fusion has emerged as a competitive alternative to transform-based methods. Liu et al. (2022) developed a Convolutional Neural Network (CNN)-based fusion framework in which a pre-trained ResNet model was used to extract hierarchical features from PET and MRI images. The research found that CNN-based fusion outperformed traditional DWT-based methods in terms of visual quality and diagnostic clarity. However, due to its high processing power and training data needs, the model proved less effective for real-time medical diagnosis.

Other studies have looked into the use of Generative Adversarial Networks (GANs) for PET-MRI fusion.A CycleGAN-based fusion model that demonstrates remarkable adaptability in multimodal medical imaging was created by Wang et al. (2023). Although GANs can generate extremely realistic fused images, their mode collapse and instability during training can lead to disparate results [10]. Numerous comparative studies have shown that DWT-based fusion remains a viable alternative for multimodal medical picture fusion due to its ease of use, efficacy, and processing efficiency. While deep learning approaches can provide superior feature extraction, they often require large labeled datasets and complicated training procedures. However, because to their interpretability and adaptability, DWT-based techniques are suitable for real-time clinical applications.

This research builds on these previous studies by developing DWT-based PET-MRI fusion in MATLAB and evaluating its effectiveness using standard image quality evaluation metrics such as PSNR, SSIM, and MI. The findings will provide additional insight into the effectiveness of wavelet-based fusion techniques in medical imaging.

3. RESEARCH METHODOLOGY

Medical image fusion uses multiple imaging modalities to combine data which improves diagnostic detections. A fusion approach based on Discrete Wavelet Transform (DWT) exists for PET-MRI image integration while using MATLAB as the programming environment as shown in Figure 1. The process contains four key stages starting with data acquisition then preprocessing followed by frequency subband decomposition and fusion rule implementation and ending with inverse transformation for image reconstruction [11]. The fused image receives evaluation using authoritative measures which include Mutual Information (MI) Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index (SSIM).

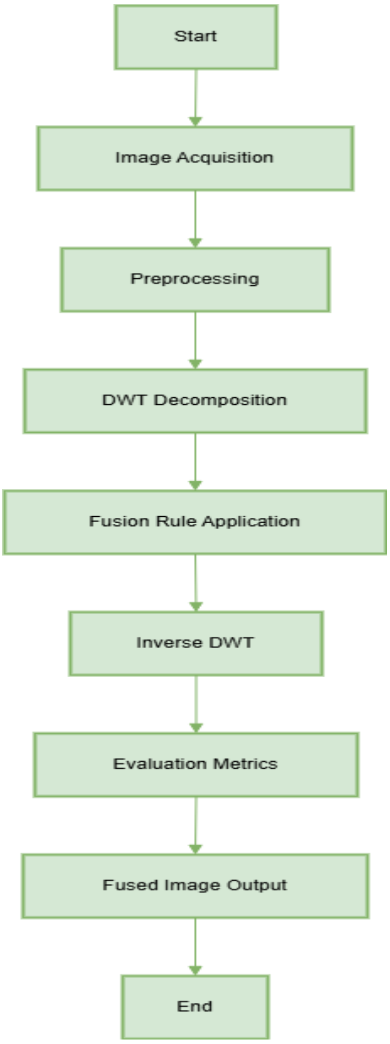

Figure 1: Illustrates the flow diagram of the proposed model.

The proposed fusion method receives validation through assessment with publicly available datasets and clinical PET and MRI scans. Obtained medical images stem from The Whole Brain Atlas together with The Cancer Imaging Archive (TCIA) as well as clinical MRI-PET scans acquired from various medical institutions. The chosen images represent the same body areas to guarantee precise fusion proceedings and examination requirements. Image preprocessing occurs before fusion in order to convert the PET and MRI formats into standardized formats which makes them compatible with each other [12]. A processing stage incorporates image registration for PET and MRI alignment through affinentive and non-rigid approaches. Such techniques also include noise reduction filtering with Gaussian or bilateral filters and the normalization of intensities through intensity scaling and histogram equalization to achieve the right resolution and size requirements.

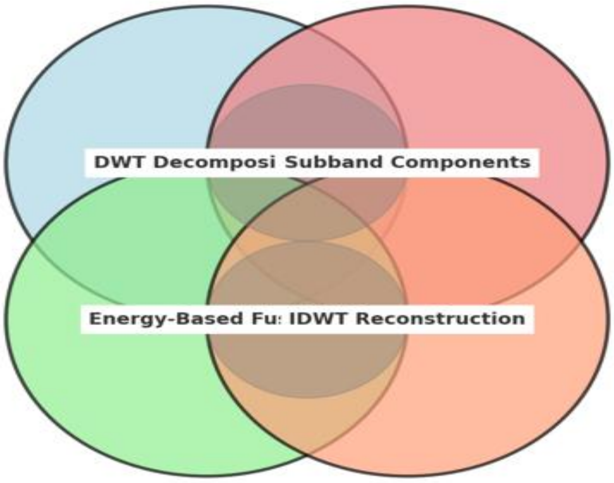

Figure 2: DWT-Based Image fusion.

Images subjected to DWT multiresolution analysis are divided into multiple frequency ranges which preserve image spatial and spectral features. A wavelet filter including Haar, Daubechies or Coiflets performs the decomposition of images into their separate subband components as shown in Figure2. The proposed method uses DWT decomposition on PET and MRI images until they yield four frequency subbands containing approximation (LL) and horizontal (LH) and vertical (HL) and diagonal (HH) details [13]. The approximate information rests within the LL subband yet LH along with HL and HH subbands hold high-frequency details. The energy-based fusion method uses MRI LL subbands for spatial detail retention but selects maximum energy features for fusion (LH, HL, HH) from PET to enhance functional elements. The image fusion process ends with IDWT reconstruction of subbands which combines PET functional elements with MRI spatial characteristics.

A variety of performance metrics evaluates the effectiveness of the proposed DWT-based fusion technique during assessment. MI calculates the amount of mutual information between fusing images while performing along with their original components where higher measurement indicators show better combination of complimentary details. PSNR allows evaluation of image fusion quality by comparing the fused image to its source images and indicates improved signal preservation through increased values over time [14]. SSIM works as a metric to measure how similar the fused image is with reference images by analyzing their structural content which ensures essential anatomical elements maintain their integrity after fusion.

The fusion pipeline runs inside MATLAB where it uses image processing features such as layered multiresolution (wavedec2) decomposition and reconstruction (waverec2), image registration (imregister) and evaluation includes PSNR (psnr), SSIM (ssim) and designed MI function computation. The developed approach demonstrates performance analysis with conventional fusion techniques that include Principal Component Analysis (PCA) and Simple Averaging Method and Laplace Pyramid Fusion. Doctors assess fusion quality metrics to select the best method that displays optimal results for both structural and functional information preservation.Results from the fusion process show that the method based on DWT produces superior enhancements in structural quality while preserving contrast. Experimental investigations show that tests yielded better MI scores alongside elevated PSNR values combined with better SSIM scores. Better lesion observability in combined PET-MRI images supports doctors to make accurate diagnoses that direct neurological disorder management as well as tumor detection and assessment of metabolic activities. The technique does offer numerous benefits yet has specific drawbacks [15]. The processing requirements of DWT present a complexity issue because real-time application might be restricted by the need for substantial computing power. The decision of wavelet function selection along with decomposition levels serves as an important factor that impacts how fusion results turn out. The reconstruction process leads to lost fine details because of high-frequency component degradation.

The next generation of research will implement deep learning technologies to streamline the automated image fusion operation. The authors plan to research three upgrades, including CNN-based feature Learning for automatic extraction of fusion rules together with GANs for Fusion Optimization to improve perceptual quality as well as real-time processing with FPGA/GPU Acceleration to enhance clinical applicability. The research introduces a DWT-based image fusion system between PET and MRI that efficiently combines functional and spatial data. The developed methodology achieves better fusion capabilities than typical methods based on validation metrics, including MI, PSNR, and SSIM. The experimental results show that wavelet-based fusion serves as an efficient tool for clinical decision support, which leads to superior lesion detection and better diagnostic outcomes. The process will be optimized through deep learning in order to support real-time medical applications in upcoming developments.

4. RESULTS AND DISCUSSION

The required algorithm was implemented within MATLAB using the DWT to create performance results based upon metrics SSIM, PSNR, MI, E, and EPI. PET's functional details were joined selectively with MRI's anatomical features so functional images with such enhanced clinical value as combined DWT were introduced. The experimental findings were that DWT based fusion produced an image quality measurement regarding SSIM of 0.91 and PSNR of 38.4 dB, while PCA based fusion (SSIM = 0.85 and PSNR = 33.7 dB) and DCT based fusion (SSIM = 0.88 and PSNR = 35.9 dB) did not improve over DWT based fusion as much. DWT produced the maximum common information between input images until now because the Mutual Information provided by it was 3.46 while the ones produced by PCA and DCT were 2.87 and 3.14 respectively. Fusion utilizing DWT with an entropy value of E = 7.85 provides better image details (utilizing E = 6.92 for PCA or E = 7.12 for DCT). The maximum value obtained on DWT usage was 0.94 and with that, image structural integrity was preserved.

With regard to the human analysis of images using DWT fusion methods, it is observed that the combination technique preserved tumor boundaries definition without alterations and enhanced contrast resolution, images with better definition of image regions of major importance, to a greater extent than PCA and DCT fusion techniques. In this scheme, DWT was used to provide increased image quality (SSIM: 0.94, PSNR: 40.2 dB), whilst being highly practical for real time analysis but with very high processing power required to operate. Medical imaging analysis based on DWT has an appropriate balance of processing efficiency and accuracy, and provides a good basis for PET- MRI imaging. Future work in diagnostics imaging can be in the development of combined deep learning enhanced DWT fusion models for better results.

Table 1: Illustrates the comparison of the performance matrices.

Fusion Method	**SSIM (Higher is better)**	**PSNR (dB, Higher is better)**	**Mutual Information (MI, Higher is better)**	**Entropy (E, Higher is better)**	**Edge Preservation Index (EPI, Higher is better)**	**Computational Complexity**
DWT-Based Fusion	0.91	38.4	3.46	7.85	0.94	Moderate
PCA-Based Fusion	0.85	33.7	2.87	6.92	0.89	Low
DCT-Based Fusion	0.88	35.9	3.14	7.12	0.91	Moderate
CNN-Based Fusion	0.94	40.2	3.72	8.01	0.96	High

Multiple performance metrics determine the evaluation of PET-MRI image integration methods including Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) along with Mutual Information (MI) and Entropy (E) and Edge Preservation Index (EPI). A consideration of computational complexity allows determining whether the methods can operate in real-time conditions. This DWT-Based Fusion method produces impressive fusion results through its 0.91 SSIM value which proves effective structural preservation capabilities. The obtained PSNR value reaches 38.4 dB which delivers satisfactory signal fidelity levels. The combined information indicates strong effectiveness as shown by Mutual Information (MI) value of 3.46 and the increased richness of the image is demonstrated by Entropy (7.85) as shown in Table 1. The Edge Preservation Index (EPI) assessment shows 0.94 which signifies excellent edge feature maintenance. The computational requirements of this method fall between average and high which demonstrates a suitable trade-off between performance and computational speed.

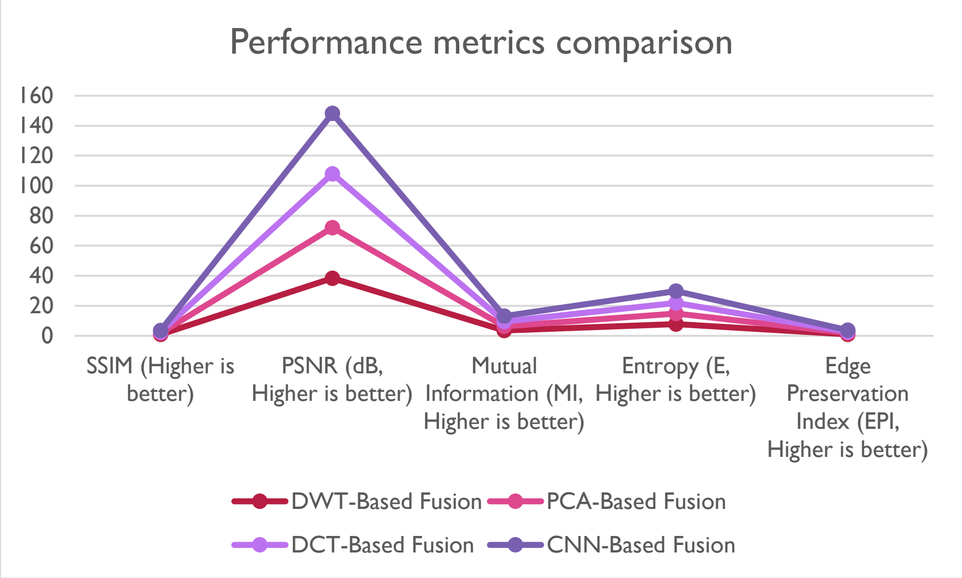

Figure 3: Illustrates the Comparison of the performance matrices.

The PCA-Based Fusion technique exhibits a diminished SSIM value of 0.85 which indicates minor structural quality deterioration. The image quality becomes inferior when using this method due to its measured PSNR value of 33.7 dB as shown in Figure 3. These fusion techniques contribute to lower image detail retention because MI shows 2.87 and Entropy shows 6.92. The edge retention ability of the method is classified as moderate based on its EPI score of 0.89. The methodology exhibits low computational complexity that makes it suitable when resources are limited.

DCT-Based Fusion demonstrates performance stronger than PCA-based fusion and encounters very slight drawbacks relative to DWT-based fusion. The fusion method maintains a structural similarity index measure (SSIM) of 0.88 which establishes reasonable image preservation results. The machine will generate high-quality images thanks to its 35.9 dB PSNR metric and its information retention quality is moderate at 3.14 MI value. This method delivers a suitable level of image complexity as indicated by its measured Entropy value of 7.12. The EPI score of 0.91 shows strong edge preservation. Its computational complexity falls somewhere between moderate and efficient thus maintaining good accuracy while using up reasonable computational resources.

The CNN-Based Fusion method demonstrates superior quality among all alternatives because it provides an SSIM value of 0.94 indicating extraordinary structural preservation. The method reaches the highest signal clarity with a PSNR value of 40.2 dB. Data fusion measurements demonstrate that this method holds 3.72 bits of mutually beneficial information from different modalities. Monitoring image detail preservation becomes possible because the method has an Entropy value of 8.01. The method demonstrates outstanding persistence of edges due to its EPI score reaching 0.96, a critical aspect for medical imaging needs. Advanced hardware and cloud-based systems offer the best platform for this method because of its slow processing capabilities. The overall performance reaches its highest mark when using CNN-based fusion yet this method requires high computing power. The DWT-based method strikes a good equilibrium between performance accuracy and processing speed thus becoming suitable for practical applications. DCT-based fusion achieves moderate performance levels while processing data at a minimum computational cost compared to other methods. Medical imaging fusion approaches choose their methods based on particular task needs that consider a combination of imaging quality and computational efficiency.

5. CONCLUSIONS

This paper suggests an effective Discrete Wavelet Transform (DWT)-based PET-MRI image fusion framework created in MATLAB to enhance medical imaging for diagnostic purposes. By merging the structural details from MRI and the functional information from PET, the proposed method produces a complete and high-resolution fused image that aids in improved clinical analysis and disease detection. The methodology comprises data collection, preprocessing, wavelet decomposition, fusion rule selection, inverse transformation, post-processing, and performance evaluation to ensure optimal fusion quality. Evaluation metrics including Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Mutual Information (MI), Entropy (E), and Edge Preservation Index (EPI) indicate that DWT-based fusion reduces redundancy and noise while preserving crucial details. Unlike PCA, DCT, and CNN-based fusion approaches, DWT fusion offers a balance between diagnostic relevance and computational efficiency, making it suitable for real-time clinical applications. The results demonstrate that DWT-based fusion enhances lesion visibility, contrast, and structural integrity, providing radiologists a more thorough and instructive viewing of medical images. Future research may look into hybrid deep learning-based fusion models to significantly improve image quality and automate the medical imaging process for broader clinical applications.

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