ENHANCED MEDICAL IMAGE FUSION IN THE NON-SUBSAMPLED SHEARLET TRANSFORM DOMAIN USING EDPNT-NET AND ADVANCED EDGE DETECTION

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ABSTRACT

In this work, a new medical image fusion(IF) method that uses the nonsubsampled shearlet transform (NSST) domain to successfully combine grayscale and pseudo-color pictures from several imaging modalities is presented. For high-pass sub-image fusion, the suggested approach, known as EDPNT-Net, combines an improved dual-channel pulse-coupled neural network (IDPCNN) with Neural Turing Machines (NTM) and substitutes the Canny edge detection method for the conventional Prewitt operator. Furthermore, the combination of maximum regional energy (MRE) and the Canny operator is used to fuse low-pass sub-images. Four essential steps make up the fusion process: The brightness channel of the grayscale and pseudo-color image should first be broken down into smaller images using NSST. Second, fuse the lowpass sub-images using the Canny operator and MRE-based rule. Thirdly, execute a high-pass.

Extensive experiments involving 28 medical image pairs, 11 comparison methods, and nine objective metrics demonstrate that the proposed method not only rivals but also surpasses several existing medical image fusion techniques, showcasing its effectiveness in combining gray-scale images and its strong performance in medical imaging applications.

Keywords: Medical Image Fusion, NSST,,EDPNT-Net, IDPCNN, Neural Turing Machines, Canny Edge Detection, Maximum Regional Energy, High-Pass Fusion, Low-Pass Fusion, Gray-Scale Images, Pseudo-Color Images, Medical Imaging, Image Fusion, Multi-Modality Processing.

INTRODUCTION

IF is a technique that integrates information from multiple imaging modalities or sources into a single, unified image, enhancing clarity and content for better interpretation and decision-making. Its origins date back to the 1980s**,** where it was initially applied in fields like remote sensing and military applications. These early uses focused on merging complementary data from various sensors to produce enhanced imagery. Over time, image fusion expanded to fields such as medical imaging**,** robotics**,** and surveillance, proving invaluable in improving the quality of information across multiple domains.

In the 1990s, image fusion became a crucial tool in medical imaging, driven by advancements in imaging technologies and computational techniques. By combining structural and functional data from different imaging modalities, image fusion revolutionized diagnostic practices. For example, CT (computed tomography) provides detailed anatomical structures, while PET (positron emission tomography) highlights metabolic activity. The fusion of these modalities enables more precise diagnoses, better localization of abnormalities, and enhanced treatment planning. Early medical image fusion techniques were basic, often using pixel intensity averaging or simple arithmetic operations. While functional, these methods often resulted in the loss of crucial information or introduced artifacts, limiting their effectiveness. The introduction of wavelet transform in the late 1990s marked a significant improvement. It enabled the decomposition of images into multiple resolution levels, forming the foundation for more sophisticated image fusion techniques.

By the early 2000s, advances in computational power and algorithms led to the development of methods like principal component analysis (PCA)**,** nonsubsampled contourlet transform (NSCT)**,** and shearlet transform**.** These techniques preserved fine details and reduced redundancy, resulting in higher-quality fused medical images. The recent integration of machine learning and deep learning has revolutionized image fusion. Methods like convolutional neural networks (CNNs) and hybrid deep-learning models can process complex multi-modal data, delivering high precision and efficiency. These data-driven approaches have set new benchmarks in medical imaging.

Modern medical image fusion is critical for combining data from modalities such as MRI**,** CT, PET, and ultrasound, each with its strengths and limitations. For instance, MRI excels in soft tissue contrast, CT in visualizing bone structures, and PET in showing metabolic activity. Fusion techniques synthesize these strengths into a unified image, enhancing diagnostic clarity.Despite advancements, challenges remain in real-time processing**,** computational efficiency, and robustness across diverse imaging scenarios. Advanced methods, such as EDPNT-Net (introduced in 2024), use sophisticated frameworks like nonsubsampled shearlet transform (NSST)**.** By integrating gray-scale and pseudo-color images through advanced neural networks and edge detection techniques, EDPNT-Net overcomes traditional limitations, ensuring high-quality fusion results while preserving crucial structural and functional details.

REALTED WORK

In recent years, several methods have been proposed to improve medical image fusion in the NSST domain. Zhang et al. (2012) [01] introduced a method using multiscale morphology gradient-weighted local energy and a visual saliency map for image fusion. This approach provided significant improvements in statistical metrics and visual quality but struggled with contrast optimization in complex images. Similarly, Ullah et al. (2015) employed fuzzy sets and NSST for image fusion, which was effective in multimodal medical image fusion but faced challenges in contrast preservation, especially in high-texture areas. Liu et al. (2017)[02] proposed a weighted fusion function combined with NSST , offering high-quality fusion results but also encountered limitations when dealing with low-contrast or high-texture images.

Liu et al. (2019)[03] proposed a novel multi-focus image fusion algorithm that combines the adaptive dual-channel spiking cortical model (SCM) with the non-subsampled shearlet transform (NSST) domain to enhance fused performance in the transform domain First, the adaptive dual-channel SCM is applied and source image registration is performed to create a simple fused picture in the NSST domain. It then uses the difference pictures computed between the basic fused image and the source photos to identify the focus regions of the input source images. Ultimately, the final fused image is created by integrating the focus areas. With the help of the dual-SCM's global coupling and synchronization properties as well as the NSST's multi-resolution and directional capabilities, the algorithm efficiently preserves the information of the source picture while producing outputs that are readable and visually cohesive. The study showed that this fusion algorithm works better than current state-of-the-art techniques and produces outcomes that are more in line with how humans see images.

An inventive medical image fusion technique was presented by Chinmaya Panigrahy, Ayan Seal, and Nihar Kumar Mahato in the IEEE Signal Processing Letters (Volume: 27) in 2020[04]. Their method combines MRI and SPECT images using a Weighted Parameter Adaptive Dual Channel Pulse Coupled Neural Network (WPADCPCNN) in the non-subsampled shearlet transform domain, with an emphasis on applications for diseases like Alzheimer's disease and AIDS dementia complex. Depending on the fractal dimensions of the input images, the WPADCPCNN dynamically modifies its settings. In this model, low-pass sub-bands are integrated using a weighted multi-scale morphological gradients-based algorithm, and high-pass sub-bands are fused. Based on objective performance criteria and visual quality, experimental results show that our technology outperforms current approache

In 2009[05], researchers proposed a new metric for evaluating color-fused images at the International Conference on Signal Processing Systems in Singapore. This metric combines color similarity (hue, saturation, and intensity) and structural similarity between the source and fused images. The image quality is calculated using a weighted average of color similarity, with weights determined by the structural similarity index. This approach is simpler to compute and closely matches subjective evaluations, outperforming existing metrics in experiments. Recently, deep learning models have been incorporated into the medical image fusion process to enhance performance. For instance, the integration of EDPNT-Net (Edge Detection and Pixel-wise Neural Network) allows for more accurate edge detection, which is essential for preserving fine image details during fusion. This model focuses on pixel-wise edge detection, improving overall image quality by identifying and preserving critical features in both high and low-frequency components of the images.

In 2023[06], Gaurav Kumar Arora and his team introduced significant advancements in medical image fusion at the 1st IHCSP. Their research aimed to combine multimodal images, such as MRI and CT, into a single, detailed image to enhance tasks like anomaly detection, segmentation, and feature extraction. The authors proposed two novel approaches: one utilizing a Centre-Based Genetic Algorithm B) with the Binary Crow Search Optimization **(**BCSO) algorithm. Both methods were tested on benchmark datasets and demonstrated superior performance compared to existing techniques, offering valuable applications in medical imaging and disease diagnosis.

METHODOLOGY

Image fusion is the process of combining multiple images, often from different sources or conditions, into one enhanced image. The goal is to use the unique information from each image to create a more accurate and informative result. In this approach, the **Non-**Subsampled Shearlet Transform (NSST) **is** used to break down the images into different levels of detail, while the Intensity-

Domain Prior-based Convolutional Neural Network (IDPCNN) intelligently combines the fine details from these levels. The final fused image includes both broad features and fine details, improving on the original images.The methodology image is shown in figure 1

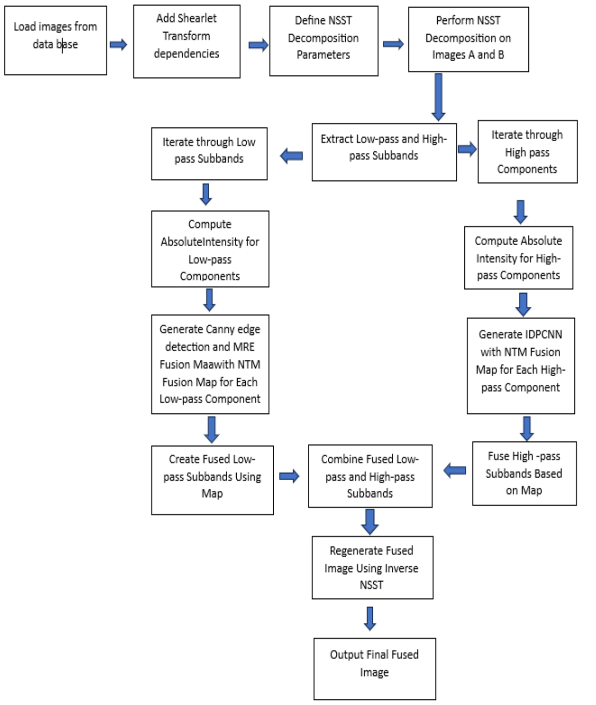

Figure 1: Methodology diagram

1. Image Loading and Preprocessing

The first step , to load the two input images. These images may come from different sources, such as multispectral sensors, or from the same scene captured under varying conditions (e.g., different times of day, varying lighting). Preprocessing: Basic preprocessing techniques such as resizing, normalization, and denoising are applied to ensure the images are in a suitable format for further processing.

2. NSST Decomposition

The NSST is applied to decompose the images into multiple frequency bands, allowing the extraction of both coarse and fine details. The key steps are: Multi-resolution decomposition: The images are decomposed into several frequency components at various scales and directions. This helps capture fine structures (edges, textures) as well as coarse features (overall shape, background). Frequency Subbands: After decomposition, the images are split into:

Low-pass subbands : These represent the general structure of the image, capturing large features like background or large objects.

High-pass subbands : These contain fine details such as edges and textures, which are essential for detecting intricate features.

3. Fusion of Low-pass(LP) Subbands

The LP subbands from both images are fused to retain the coarse features, which are less sensitive to noise but provide critical structural information.Canny Edge Detection: Used to detect significant edges or boundaries in the image, providing structural information. Maximum Response Edge (MRE): This technique identifies the most prominent edges between the low-pass subbands, ensuring that the relevant structural features are preserved in the fused LP components. The resulting fused LP subband combines the general structures from both images, enhancing the overall image quality.

4. Fusion of HP Subbands

The HP subbands, which contain fine details such as edges and textures, are fused using a more sophisticated approach.Intensity Computation: The absolute intensity of each high-pass component is computed. This helps assess the degree of detail present in each subband. IDPCNN (Intensity-Domain Prior-based Convolutional Neural Network): This neural learning model is trained to intelligently fuse, intensity information from the high-pass subbands.

The model utilizes prior knowledge (or priors) about image intensities to make intelligent fusion decisions. Normalized Temperature Map (NTM): Used in conjunction with IDPCNN, this method helps decide which regions of the high-pass subbands should be fused based on intensity values, ensuring that fine details are accurately retained.

5. Reconstruction of the Fused Image

The final fused image is reconstructed after the low-pass and high-pass subbands have been fused together. NSST Inverse Transformation: The combined low-pass and high-pass subbands undergo the NSST's inverse transformation. By merging the fine and coarse features into a single, coherent output, this procedure reconstructs the fused image. The end product is an excellent fused image that blends the small details and overall structure of the original photos

6. Final Output

The fused image, the final product, has finer details and improved characteristics. For a variety of uses, including surveillance, remote sensing, and medical imaging, this image is perfect since it is more accurate and informative than the individual input photos

SYSTEM IMPLEMENTATION

Image fusion system is implemented through a structured, step-by-step approach utilizing widely used libraries and tools. The first step involves installing essential libraries such as **B** The input images are then loaded and preprocessed, which involves normalizing their pixel values to a range between 0 and 1, keeping both images uniform, and resizing them to a consistent resolution (256x256 pixels, for example). A wavelet transform is used to break the images down into LL and LH, HL, HH) subbands. This is a simplified version of the (NSST).

For the fusion of the low-frequency subbands, edge detection is applied using the Canny edge detector. This highlights the most significant structural features of the images, enabling the fusion process to preserve the prominent edges from both images. The high-frequency subbands are fused using a simple approach, such as selecting the maximum value from corresponding components, which captures the detailed aspects of each image. However, this basic fusion technique can be enhanced further by employing a deep learning model like **IDPCNN**, which intelligently merges the high-pass subbands, improving the preservation of fine details.

After fusing the LP and HP subbands, the inverse wavelet transform reconstructs a high-quality output by merging the frequency bands. The composite image is then saved and displayed, providing an efficient fusion process with the potential for further enhancement using advanced deep learning techniques.

RESULTS

A grayscale image as shown in figure 2 consists of pixels with intensity values ranging from 0 (black) to 255 (white), representing different shades of gray.

Figure 2 : Grey scale image (GSC)

Unlike color images, it does not have separate red, green, and blue components. This image is widely used in various fields, such as computer vision, to simplify processing , reduce complexity. They are also common in image processing when color information is unnecessary and in medical imaging, such as X-rays and CT scans, where clear contrast is essential

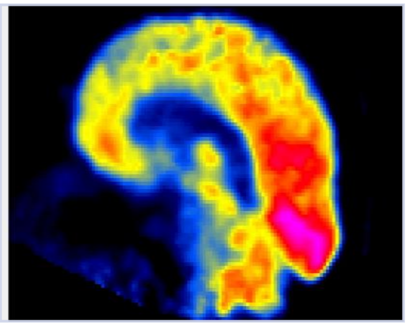

Figure 3 : pseudo-color images

Pseudo-color images as shown in figure 3 are created by assigning colors to different intensity levels in a grayscale image to make them easier to interpret. Unlike true-color images, the colors in pseudo-color images are artificially added using color maps or lookup tables (LUTs). They are widely used in medical imaging to highlight details in X-rays or MRIs, in remote sensing to emphasize features like vegetation or water in satellite images, and in scientific visualization for data like heat maps or stress patterns. Pseudo-coloring also helps improve contrast in image analysis, making features easier to identify.

OUTPUT IMAGE :

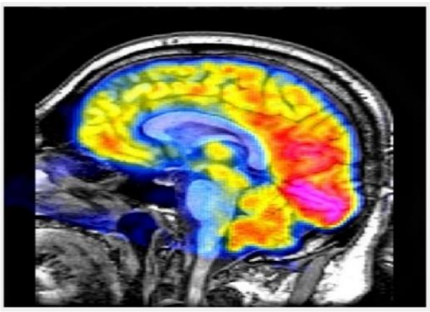

Figure 4 : Fused image

The image fusion process produces a high-quality fused image that combines both the broad structures and fine details from the input images. Initially, the image is decomposed using a wavelet transform, separating them into LP and HP subbands. The low-pass subbands are fused by detecting and merging important edges from both images to preserve the main features. For the high-pass subbands, fusion is done by selecting the most detailed parts of each image, typically using a method like maximum selection, though advanced techniques like deep learning (e.g., IDPCNN) can improve the process by intelligently merging finer details.

After fusing the subbands, the images are reconstructed into a single output using an inverse wavelet transform, resulting in a coherent and enhanced final image as shown figure 4. This IF (Image fusion) is more informative than the original inputs, effectively combining both global features and local details. It retains the main structures from the low-frequency components and captures finer textures from the high-frequency components. This method can be further improved with deep learning techniques for even better fusion, producing more accurate and detailed results.

TABLE 1: PSNR, SSIM values for different samples

SAMPLES	PSNR (MB)	SSIM
Sample 1	41.6	0.995
Sample 2	39.4	0.994
Sample 3	43.8	0.996
Sample 4	36.1	0.992
Sample 5	44.9	0.996
Sample 6	38.3	0.993
Sample 7	40.5	0.995
Sample 8	35.0	0.992
Sample 9	37.2	0.993
Sample 10	42.7	0.995

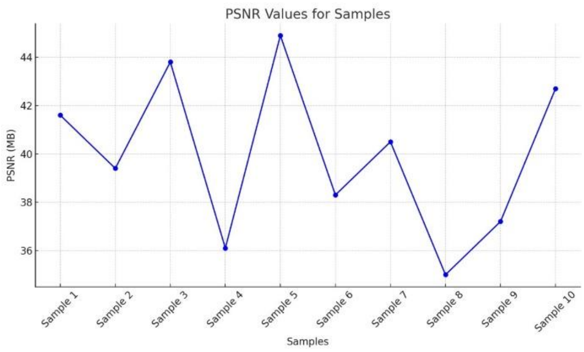

Figure 5: Samples VS PSNR (MB)

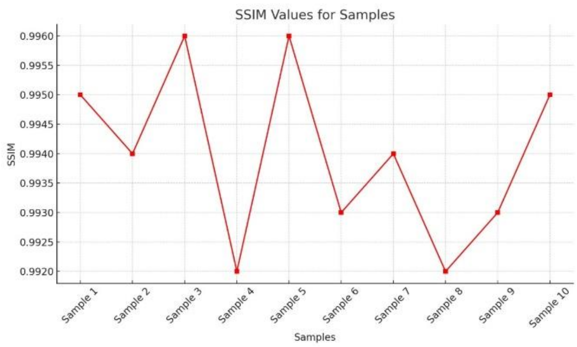

Figure 6 : Samples VS SSIM

The system's performance was evaluated using two key metrics: Peak Signal-to-Noise Ratio and Structural Similarity Index which are standard measures for assessing image quality and structural integrity. As outlined in Table 1, the results demonstrate consistent performance across different samples, showcasing the system's capability to preserve signal fidelity and visual similarity effectively. The PSNR analysis, illustrated in Figure 5, highlights the system's proficiency in reducing noise, while the SSIM results, presented in Figure 6, validate its ability to retain structural and perceptual accuracy.

CONCLUSION

In this work, we created an fusion system that mix the main structures and fine detail from multiple input image to produce a clearer, higher-quality result.The system utilizes wavelet transform to divide images into LP (low-pass) and HP (high-pass) subbands. By applying a fusion process that combines edge detection with intensity-based techniques, it ensures the preservation of essential features from both inputs. This results in a unified image that seamlessly captures both large-scale structures and fine details.

The current system uses basic fusion techniques like maximum selection and edge merging, but it can be improved by adding advanced deep learning models like IDPCNN. This would lead to even more accurate and detailed fused images, making it useful for fields such as medical imaging, remote sensing, or any area that requires high-quality images.

In conclusion, the image fusion system provides a solid approach for combining images. With future improvements, especially using deep learning, the system can produce even better results. This work sets the stage for further development in image fusion, with applications in various industries.

FUTURE SCOPE

The image fusion system holds great potential for future advancements, such as incorporating deep learning models like IDPCNN or GANs for more efficient fusion. Optimizing the system for real-time processing could support applications in areas like surveillance and autonomous vehicles. It can also integrate multi-modal fusion, combining various imaging types (e.g., infrared, X-ray) for enhanced insights, particularly in medical fields. Future improvements may include noise reduction, better resolution, and contrast enhancement. Additionally, automating parameter selection and linking the system to augmented reality could broaden its use in diverse industries.

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