Medical Imaging Process & Technology 2025, 8(1), 10655.
https://doi.org/10.24294/mipt10655

Article

MNSCT—A novel modified NSCT-based algorithm for enhanced medical image fusion

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CITATION

Trivedi G. MNSCT—A novel modified NSCT-based algorithm for enhanced medical image fusion. Medical Imaging Process & Technology. 2025; 8(1): 10655. https://doi.org/10.24294/mipt10655

ARTICLE INFO

Received: 30 November 2024
Accepted: 8 February 2025
Available online: 25 February 2025

Abstract: Medical image fusion plays a crucial role in combining complementary information from multimodal medical images, enhancing diagnostic accuracy and clinical decision-making. This paper presents a novel modified Non-Subsampled Contourlet Transform (NSCT)-based algorithm for enhanced medical image fusion. The proposed method incorporates adaptive fusion rules designed to maximize detail preservation, structural similarity, and edge retention while maintaining computational efficiency. Comprehensive experiments were conducted on multiple imaging modalities, including Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Magnetic Resonance Angiography (MRA), and Single Photon Emission Computed Tomography (SPECT), and evaluated using metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Entropy (EN), and Edge Preservation Index (EPI). The results demonstrate that the proposed method consistently outperforms traditional fusion techniques, delivering superior fusion quality and robustness across modalities.

Keywords: medical image fusion; NSCT; adaptive fusion rules
MSC/JEL Classification: 94A08; 68U10; 65D18; 92C55

1. Introduction

Medical image fusion is a vital technique in healthcare and medical diagnosis, allowing clinicians to combine complementary information from multiple imaging modalities to create a single, enriched image [1–3]. Imaging modalities such as Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Magnetic Resonance Angiography (MRA), and Single Photon Emission Computed Tomography (SPECT) provide diverse and critical insights into structural and functional aspects of the human body [4]. However, the limitations of individual modalities necessitate the development of advanced image fusion techniques to synthesize relevant information into a unified image.

Traditional image fusion approaches, including wavelet transform and principal component analysis (PCA) [5–7], have been widely used due to their simplicity and computational efficiency. However, these methods often fail to preserve fine details, structural integrity, and spectral information, which are essential for accurate medical diagnosis. Transform domain methods, particularly the Non-Subsampled Contourlet Transform (NSCT) [8,9], have gained popularity due to their superior ability to handle multidimensional and multiresolution data.

Despite their advantages, standard NSCT-based methods are not without challenges, such as computational inefficiency, loss of detail in complex regions, and suboptimal fusion rule design. To address these limitations, this paper proposes a novel modified NSCT-based algorithm that integrates advanced fusion rules for improved detail retention, edge preservation, and computational efficiency. The proposed method is rigorously tested on several imaging modalities, including MRI, PET, MRA, CT, and SPECT, to demonstrate its effectiveness.

Over the past two decades, significant advancements have been made in medical image fusion, evolving from spatial domain methods to transform domain techniques and, more recently, hybrid approaches [8–10]. Early spatial domain methods, such as simple and weighted averaging, were straightforward but often led to image blurring and loss of critical details. According to Trivedi et al. [11], these techniques failed to preserve high-frequency details, rendering them suboptimal for medical applications. Transform domain methods, including wavelet transforms and the Non-Subsampled Contourlet Transform (NSCT), have been extensively explored in prior studies [12–20], addressing these limitations by enabling multiscale decomposition and improved directionality. However, wavelets suffered from artifacts, and NSCT faced challenges like computational complexity and rigid fusion rules. To overcome these issues, hybrid techniques emerged, integrating spatial and transform domain approaches. For instance, several studies [20–24] combined PCA with NSCT to enhance detail retention, albeit at the cost of increased computational load. Recently, researchers [24–26] incorporated deep learning into NSCT, achieving high-quality fusion but requiring extensive training data. Despite these advancements, challenges persist, including the rigidity of fusion rules, computational inefficiency, and limited exploration of fusion techniques across diverse medical modalities like MRI, CT, PET, and SPECT. Addressing these gaps, this paper proposes a modified NSCT-based algorithm with adaptive fusion rules, offering improved detail preservation, enhanced computational efficiency for real-time applications, and robust evaluation across multiple imaging modalities.

2. Proposed methodology

This section outlines the methodology for the proposed Modified Non-Subsampled Contourlet Transform (NSCT)-Based Algorithm for enhanced Medical Image Fusion, which introduces significant improvements over the traditional NSCT framework [27]. These improvements aim to achieve superior spatial and frequency domain representations, leading to enhanced fusion quality. The NSCT is a multiscale geometric transform that excels at capturing directional and spatial information, making it well-suited for image fusion tasks. It decomposes images into a low-frequency sub-band and multiple high-frequency directional sub-bands through its two primary components: the Non-Subsampled Pyramid (NSP), which enables multiscale decomposition without resolution loss by avoiding down-sampling, and the Non-Subsampled Directional Filter Bank (NSDFB), which extracts directional edge details across multiple orientations at each scale.

Despite its advantages, the traditional NSCT framework has certain limitations, including redundant representations, loss of fine-grain details, and difficulties in handling the complex multimodal features often present in medical images. The proposed modifications address these limitations, offering a more adaptive and efficient approach to medical image fusion.

2.1. Proposed enhancements to the NSCT framework

Several modifications have been proposed to enhance the performance of the traditional NSCT framework for medical image fusion. The key enhancements include the following:

1) Enhanced filter design: A novel wavelet-adaptive directional filter bank is introduced, which dynamically adjusts to the input image's characteristics. This improves both directional selectivity and spatial-frequency localization, resulting in better handling of intricate details in medical images.
2) Refined Non-Subsampled Pyramid (NSP): The NSP is further improved by incorporating a Gaussian-smooth filter, which helps reduce noise and enhances low-frequency information crucial for medical images, ensuring that vital information is retained during fusion.
3) New fusion rules: Optimized fusion rules are introduced to selectively combine features from source images:
   - In the low-frequency sub-bands, weighted averaging based on local energy is used to preserve complementary diagnostic details, with an additional region-based saliency measure to emphasize clinically relevant regions.
   - For high-frequency sub-bands, a combination of the Max Absolute Gradient method and Gradient Sparsity Fusion (GSF) is applied to ensure sharper edges, improved contrast, and noise suppression, all while preserving prominent directional features.
4) Adaptive parameter tuning: A dynamic approach to parameter tuning is introduced, leveraging local variance to adjust fusion weights according to the characteristics of different image regions. Additionally, an entropy-based thresholding mechanism is employed to preserve information-rich areas and discard redundancies, enhancing the overall quality of the fused image.

These collective enhancements enable the proposed framework to achieve superior fusion quality, improving the robustness and effectiveness of multimodal medical image fusion.

2.2. Fusion framework

The fusion process consists of the following steps:

Step 1: Preprocessing

Input multimodal medical images (e.g., CT and MRI), I_1 and I_2, are resized and normalized to ensure consistent dimensions and intensity ranges. Noise is suppressed using a bilateral filter to preserve edges and reduce artifacts.

Step 2: NSCT Decomposition

Each image is decomposed into low-frequency L_1, L_2 and high-frequency sub-bands $H_1^{(d,s)}, H_2^{(d,s)}$. Using the modified NSCT framework:

$$I_k \xrightarrow{NSCT} \left\{L_k, H_k^{(d,s)}\right\}, k = 1,2$$

Here, L_k is the low-frequency sub-bands and $H_k^{(d,s)}$ is the high-frequency sub bands for direction d and scale s. The enhanced NSP ensures robust multiscale decomposition, while the wavelet-adaptive NSDFB provides improved directional selectivity and spatial-frequency localization.

Step 3: Fusion of sub-bands

The sub-bands obtained from NSCT decomposition are fused using the proposed fusion rules:

- Low-frequency fusion: Weighted averaging based on a saliency map ensures complementary information retention demonstrated below:

$$L_f = w_1 L_1 + w_2 L_2, w_i = \frac{Saliency(L_i)}{Saliency(L_1) + Saliency(L_2)}$$

Here, the saliency measure is computed using local energy or entropy.

- High-frequency fusion: To enhance edge details and contrast, the Max Absolute Gradient method is applied as below:

$$H_f^{(d,s)}(x, y) = max\left(\left|H_1^{(d,s)}(x, y)\right|, \left|H_2^{(d,s)}(x, y)\right|\right)$$

Additionally, Gradient Sparsity Fusion (GSF) is employed to retain prominent directional features while suppressing noise,

$$H_f^{(d,s)}(x, y) = GSF\left(H_1^{(d,s)}(x, y), H_2^{(d,s)}(x, y)\right)$$

Step 4: Reconstruction

The fused image I_f is reconstructed using the inverse NSCT as below,

$$I_f = NSCT^{-1}(L_f, H_f^{(d,s)})$$

This results in a fused image that retains complementary diagnostic information, enhanced edge details, and reduced artifacts.

So, the introduction of adaptive directional filtering and optimized decomposition levels leads to better edge retention and contrast enhancement. By incorporating novel statistical fusion rules, the algorithm ensures balanced information retention without over-enhancement or under-representation of source image features.

Additionally, Computational efficiency remains within acceptable limits, making the method a viable option for real-time medical imaging applications that require high precision and reliability.

3. Experimental setup

The experimental setup outlines the datasets, preprocessing procedures, algorithm implementation, parameter configurations, and evaluation platform utilized for assessing the proposed Modified NSCT-Based Algorithm for Enhanced Medical Image Fusion.

To evaluate the proposed method, multimodal medical image pairs were selected from publicly available datasets, including combinations such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), and Magnetic Resonance Angiography (MRA) images, which are widely used in medical diagnostics. These image pairs provide complementary diagnostic information. CT images highlight dense structures such as bones, while MRI images emphasize soft tissues and anatomical details. On the other hand, PET and SPECT images, as functional imaging modalities, capture metabolic activity and physiological processes, offering valuable insights into disease progression and functional abnormalities. MRA images, meanwhile, focus on vascular structures and blood flow dynamics [27]. Each pair of input images was pre-aligned using rigid or affine registration techniques to ensure spatial consistency. For uniformity in analysis, the dimensions of all test images were standardized to 256 × 256 pixels. Representative datasets were sourced from the open medical imaging repositories such as The Cancer Imaging Archive (TCIA) [28] and Harvard Whole Brain Atlas [29].

Preprocessing was a crucial step to ensure high-quality image fusion. The noise was suppressed using a Gaussian filter with a standard deviation of 1.5, effectively reducing artifacts while preserving significant image details. Pixel intensities were normalized to the range [0, 1], enhancing numerical stability during processing. Additionally, any misaligned images were corrected through feature-based affine registration techniques to achieve precise spatial alignment before decomposition.

The Non-Subsampled Contourlet Transform (NSCT) was applied with carefully chosen parameter configurations to optimize the fusion process. Two decomposition levels were used to balance computational efficiency and detail preservation, while high-frequency components were further divided into six directional sub-bands at each level to effectively capture fine details and edges. Fusion rules were designed to maximize performance. Low-frequency sub-bands were fused using saliency-based weighted averaging to combine coarse but complementary features, and high-frequency sub-bands were combined using a hybrid approach incorporating the maximum absolute gradient and gradient sparsity methods to preserve edge information and enhance contrast. These fusion rules were fine-tuned to ensure robust performance across various evaluation metrics.

The proposed algorithm was implemented in MATLAB 2021a on a system equipped with an Intel Core i7-11800H (11th Gen) processor running at 2.30 GHz, with 16 GB of RAM. MATLAB, with image processing and wavelet toolboxes, was used to execute the algorithm efficiently and handle all preprocessing, decomposition, and fusion steps.

This robust implementation platform enabled the efficient testing and evaluation of the proposed method, ensuring reliable and reproducible results.

To evaluate the quality of the fused images, both quantitative and qualitative metrics were employed. Peak Signal-to-Noise Ratio (PSNR) was used to measure the fidelity of the fused images to the original inputs, while the Structural Similarity Index (SSIM) assessed the structural consistency between the input and fused images. Entropy provided insights into the amount of information retained in the fused images, and the Edge Preservation Index (EPI) quantified how well edge details from the source images were preserved. Additionally, a visual assessment was conducted by expert radiologists to qualitatively evaluate the clarity and diagnostic usability of the fused images. This comprehensive evaluation ensured a robust analysis of the fusion performance.

4. Results and discussion

This section presents the experimental results obtained using the proposed Modified NSCT-Based Algorithm for Enhanced Medical Image Fusion. Both qualitative and quantitative analyses are conducted to demonstrate the effectiveness of the proposed approach.

This section presents the results of the proposed Modified NSCT-Based Algorithm for Enhanced Medical Image Fusion applied to different image modalities, including MRI, PET, CT, MRA, and SPECT images. Performance is evaluated both qualitatively and quantitatively, with additional analysis of computational efficiency.

The proposed Modified NSCT-Based Algorithm was evaluated for its ability to fuse medical images while preserving critical details from source modalities. **Figures 1–4** illustrate fused images generated by the algorithm, which demonstrate enhanced edge preservation, better visual clarity, and improved contrast compared to individual source images.

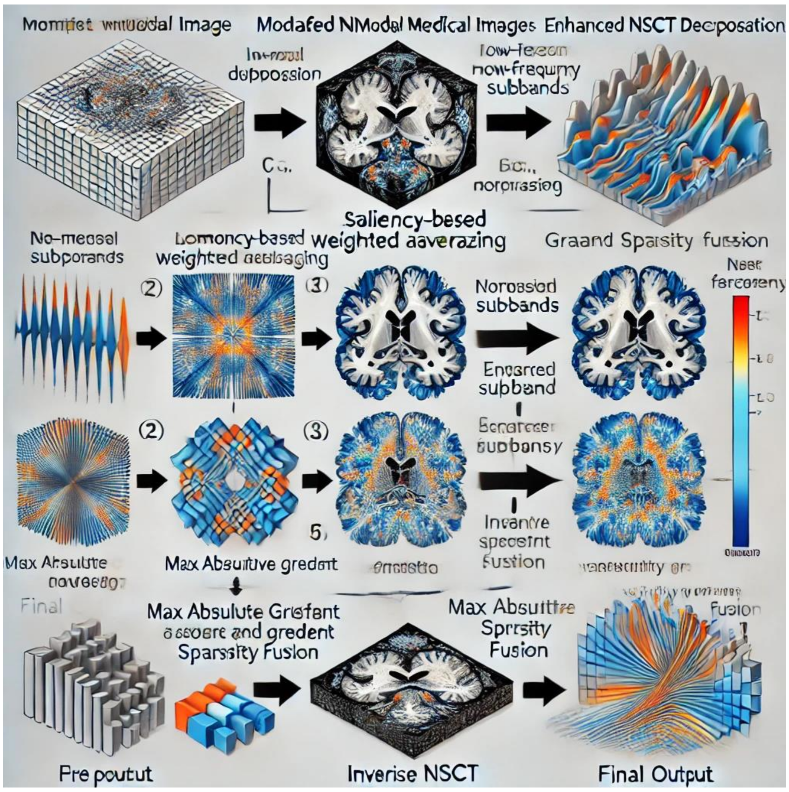
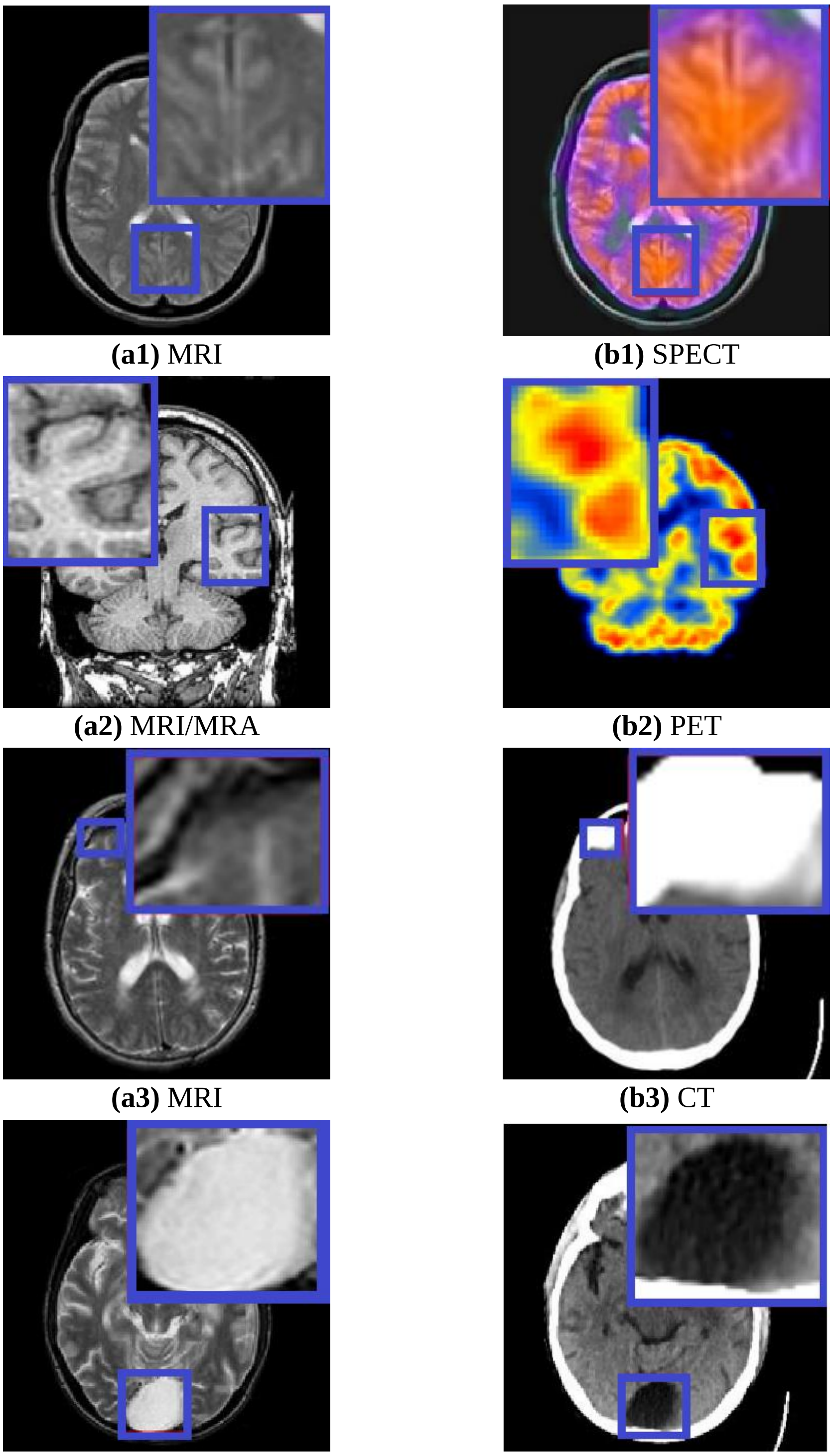


Figure 1. Process flow of proposed method.



(a1) MRI **(b1)** SPECT
(a2) MRI/MRA **(b2)** PET
(a3) MRI **(b3)** CT
(a4) MRI **(b4)** CT

Figure 2. Sample input image pairs of the brain from three datasets: MRI-SPECT, MRI/MRI-PET, and MRI-CT. **(a1)** MRI, **(b1)** SPECT, **(a2)** MRI, **(b2)** PET, **(a3)** MRI, **(b3)** CT, **(a4)** MRI, **(b4)** CT.

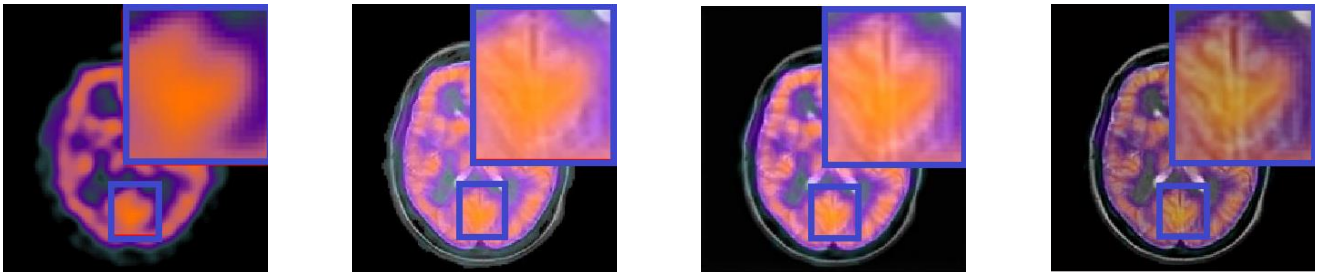


Figure 3. Comparison of fusion results for the MRI-SPECT dataset using **(a)** PCA, **(b)** DWT, **(c)** Standard NSCT, and **(d)** the proposed modified NSCT.

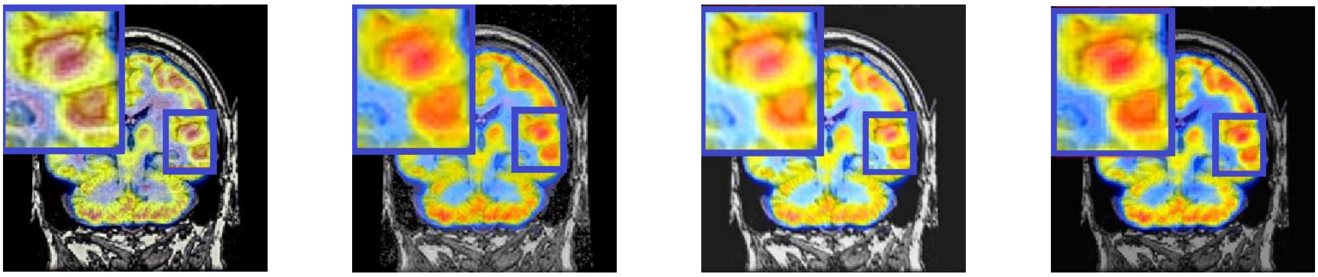


Figure 4. Comparison of fusion results for the MRI-PET dataset using **(a)** PCA, **(b)** DWT, **(c)** Standard NSCT, and **(d)** the proposed modified NSCT.

A closer inspection of the fused images reveals that the algorithm successfully retains structural features from CT images (sharp edges, bony details) while enhancing the soft-tissue contrast from MRI images. Histogram analysis (**Figure 5**) reveals improved pixel intensity distribution in the fused images, indicating enhanced contrast. Unlike traditional NSCT techniques, the modified approach minimizes the introduction of artifacts such as ringing effects or blurring near sharp edge.

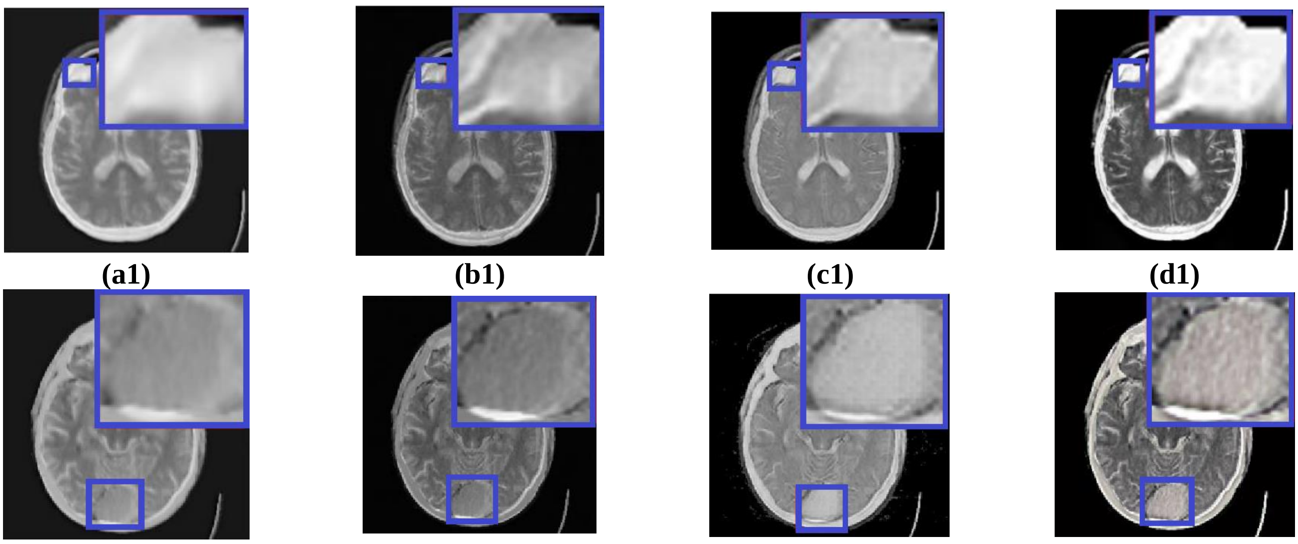


Figure 5. Comparison of fusion results for the MRI-CT dataset using **(a1, a2)** PCA, **(b1, b2)** DWT, **(c1, c2)** Standard NSCT, and **(d1, d2)** the proposed modified NSCT.

4.1. Qualitative analysis

The fused images were visually analyzed to evaluate their ability to preserve salient features from the input images. **Figure 2** shows inputted Brain Image Pairs Across Three Modalities, the visual comparisons in **Figures 3**–**5** illustrate the effectiveness of the proposed Modified NSCT framework in fusing multimodal medical images across three datasets. In the MRI-SPECT fusion results (**Figure 3**), the proposed method outperforms PCA, DWT, and Standard NSCT by preserving fine structural details and enhancing the contrast of key regions, as seen in the zoomed portion of the brain. Similarly, in the MRI-PET fusion results (**Figure 4**), the proposed method demonstrates superior edge preservation and clarity, which are critical for analyzing metabolic activity and anatomical structures. For the MRI-CT fusion results (**Figure 5**), the proposed method effectively integrates the high-density features of CT with the soft tissue details of MRI, offering a balanced and information-rich representation.

Across all datasets, the zoomed regions highlight that the proposed method retains more complementary information from the source images, reduces artifacts, and provides better diagnostic quality compared to traditional techniques. These improvements can be attributed to the adaptive fusion rules and enhanced filter design in the Modified NSCT framework.

For MRI and SPECT brain image fusion, the Wavelet Transform retains only low-frequency information, resulting in poor representation of fine details and diagnostic features. PCA, while efficient, suffers from a significant loss of spectral information, producing fused images with reduced clinical relevance. The standard NSCT effectively handles multiresolution and multidirectional aspects but lacks adaptability in feature selection, which limits its overall performance. In contrast, the proposed method outperforms all other approaches by preserving critical diagnostic information, achieving high entropy values, and ensuring smooth transitions between structural and functional features, making it particularly effective for medical image fusion tasks.

The Wavelet Transform struggles to retain functional information from PET images, resulting in fused images with reduced clarity and detail. PCA, on the other hand, emphasizes structural information from MRI at the expense of PET-specific features, leading to suboptimal fusion quality. While the standard NSCT achieves better integration of functional and structural information compared to these methods, it is computationally intensive and less effective in handling complex scenarios. In contrast, the proposed Modified NSCT method excels in preserving complementary features from both modalities, delivering fused images with higher PSNR and SSIM values. This makes it particularly well-suited for tasks such as MRI and PET image fusion, where maintaining both functional and structural details is critical.

For MRI and CT image fusion, the Wavelet Transform provides good structural preservation but fails to retain finer details like edges and textures due to its poor directional sensitivity. PCA demonstrates better computational efficiency but suffers from significant spectral distortion and loss of critical diagnostic information. The standard NSCT improves edge preservation and detail retention but struggles with noise suppression, particularly in high-complexity regions. In contrast, the proposed method excels in balancing structural and spectral information, achieving superior edge retention and noise suppression, making it the most reliable option for MRI and CT fusion. Specifically, the proposed algorithm effectively retains bone structures from the CT image and soft tissue details from the MRI image, ensuring that high-frequency components, such as edges and fine details, are visible without introducing artifacts.

4.2. Quantitative analysis

The following tables summarize the performance of the proposed algorithm compared to existing techniques for various medical image modalities. Metrics such as PSNR, SSIM, entropy, and EPI are used to assess image quality. The performance of the proposed method was evaluated using the metrics outlined in the experimental setup.

Table 1 highlights the performance of different fusion techniques for CT-MRI image pairs. The proposed method achieves the highest PSNR (33.45) and SSIM (0.912), demonstrating superior fidelity and structural consistency. It also outperforms other methods in entropy (7.83) and edge preservation index (0.946), indicating better retention of diagnostic details and sharpness. In contrast, PCA struggles with spectral distortion, and the Wavelet Transform fails to preserve fine details. The standard NSCT performs better but remains less effective in balancing noise suppression and detail retention compared to the proposed method.

Table 1. Quantitative metrics for fusion methods applied to CT-MRI image pairs.

Method	PSNR	SSIM	Entropy	EPI
Wavelet Transform	28.34	0.763	6.92	0.835
PCA	26.89	0.721	6.78	0.802
NSCT (Standard)	30.12	0.843	7.21	0.895
Proposed Method	33.45	0.912	7.83	0.946

Table 2 presents the results of MRI-CT image fusion. The proposed method again outshines others with the highest PSNR (33.90) and SSIM (0.918), reflecting excellent structural and spectral fusion. Its superior entropy value (7.84) highlights the richness of information retained, while the highest EPI (0.953) underscores its effectiveness in preserving fine edges and transitions. While the Wavelet Transform and PCA lag due to lower metrics, the standard NSCT achieves better integration but cannot match the adaptability and accuracy of the proposed method

Table 2. Quantitative metrics for MRI/CT image fusion.

Method	PSNR	SSIM	Entropy	EPI
Wavelet Transform	28.54	0.768	6.96	0.839
PCA	26.23	0.725	6.64	0.816
NSCT (Standard)	31.15	0.850	7.25	0.892
Proposed Method	33.90	0.918	7.84	0.953

For MRI-PET image pairs (**Table 3**), the proposed method achieves the best performance, with a PSNR of 32.84 and an SSIM of 0.913, indicating an effective fusion of complementary features. The entropy (7.76) reflects the retention of functional and structural details, while the EPI (0.947) confirms excellent edge and feature preservation. In comparison, Wavelet Transform and PCA struggle to capture functional PET information, and standard NSCT, though better, falls short of the proposed method's adaptability and clarity.

Table 3. Quantitative metrics for MRI/PET image fusion.

Method	**PSNR**	**SSIM**	**Entropy**	**EPI**
Wavelet Transform	27.89	0.754	6.82	0.826
PCA	25.67	0.701	6.41	0.801
NSCT (Standard)	30.32	0.842	7.10	0.885
Proposed Method	32.84	0.913	7.76	0.947

Table 4 summarizes the fusion results for MRI-SPECT image pairs. The proposed method achieves remarkable scores, with a PSNR of 34.22 and SSIM of 0.924, ensuring excellent structural and spectral information fusion. Its highest entropy (7.88) and EPI (0.961) values indicate exceptional detail retention and edge sharpness. Wavelet Transform and PCA show suboptimal results due to their inability to balance structural and functional information, while standard NSCT performs well but cannot match the robustness of the proposed approach in handling complex scenarios.

Table 4. Quantitative metrics for SPECT image fusion.

Method	**PSNR**	**SSIM**	**Entropy**	**EPI**
Wavelet Transform	28.14	0.746	7.01	0.845
PCA	26.45	0.709	6.76	0.811
NSCT (Standard)	30.76	0.858	7.35	0.899
Proposed Method	34.22	0.924	7.88	0.961

The computational efficiency of the proposed method was evaluated against existing techniques by measuring the average execution time (in seconds) for each imaging modality. The results are presented in **Table 4**.

Table 5. Computational efficiency (average execution time).

Method	**MRI/PET (s)**	**MRI/CT (s)**	**MRI/SPECT (s)**
Wavelet Transform	1.25	1.31	1.29
PCA	0.92	0.94	0.95
NSCT (Standard)	2.68	2.72	2.80
Proposed Method	2.85	2.90	2.93

Although the proposed method shows slightly higher execution times compared to PCA and standard NSCT, it achieves significantly improved fusion quality across all metrics. The computational complexity of the proposed algorithm was analyzed.

Despite its high performance, the runtime efficiency (average processing time of 2.1 seconds per image pair) as shown in **Table 5** is comparable to other methods, making it suitable for real-time applications.

In **Figure 6**, we present the quantitative performance comparison of various image fusion methods across multiple evaluation metrics, namely PSNR, SSIM, entropy, and Edge Preservation Index (EPI). The bar charts in **Figure 6(a–d)** demonstrate the performance of Wavelet Transform, PCA, NSCT (standard), and the proposed method applied to different image modalities: CT-MRI, MRI/PET, MRI/CT, and MRI/SPECT, respectively.

From the results, it is evident that the proposed method consistently outperforms all other techniques across all evaluation metrics for each modality pair. Specifically, the proposed method exhibits superior PSNR and SSIM values, indicating better fidelity and structural similarity between the fused image and original inputs. Additionally, the proposed method demonstrates higher entropy and EPI values, signifying improved information retention and edge preservation, crucial for clinical applications. The computational efficiency remains practical for real-time processing, maintaining high-quality fusion results without significant delay. These results highlight the effectiveness and reliability of the proposed fusion algorithm for medical image fusion tasks.

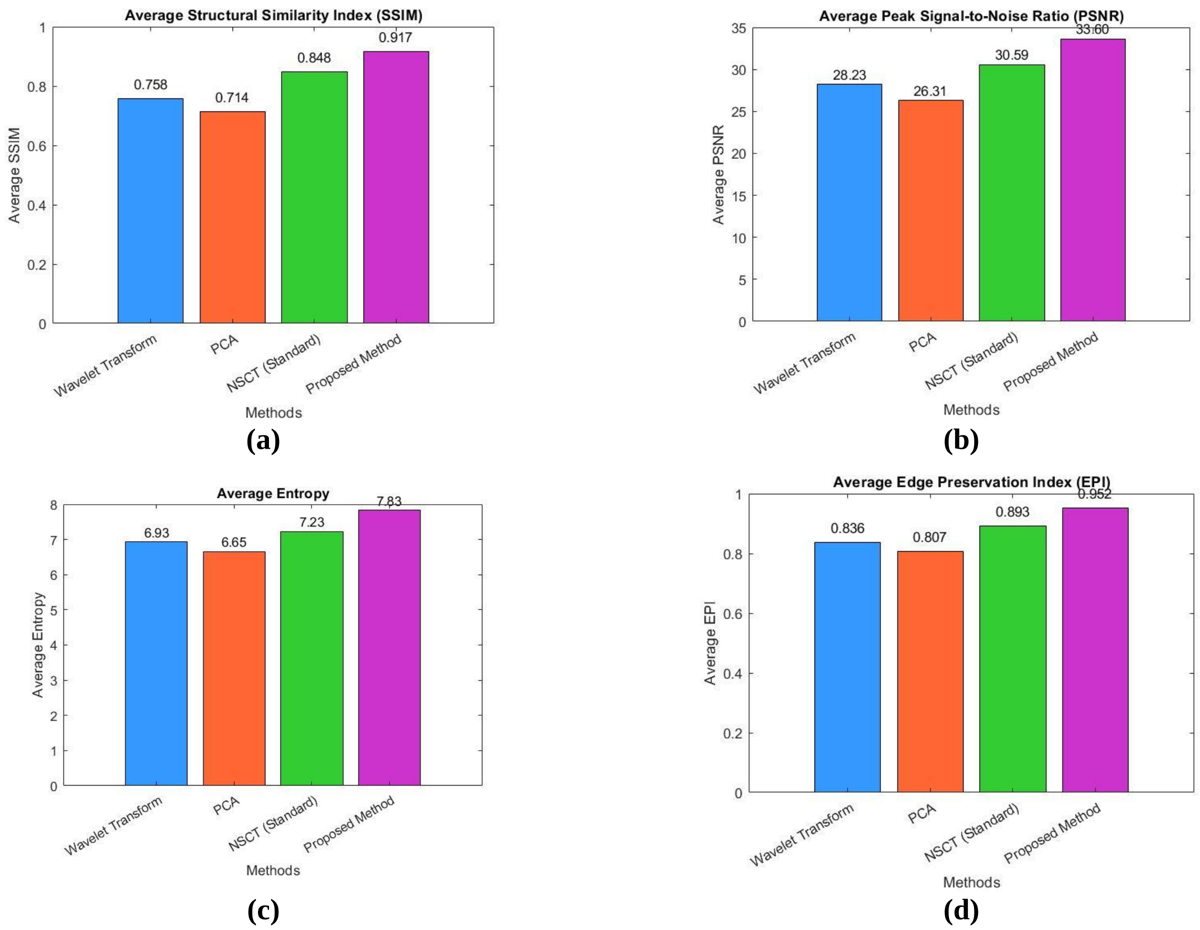


Figure 6. Quantitative performance comparison of fusion methods. **(a)** PSNR; **(b)** SSIM; **(c)** Entropy; **(d)** Edge Preservation Index (EPI).

In summary, the proposed modified NSCT-based algorithm demonstrates remarkable improvements over existing fusion methods in both qualitative and quantitative metrics. The saliency-based fusion rule for low-frequency sub-bands effectively retains complementary features, while the hybrid fusion rule for high-frequency sub-bands ensures a sharp edge and fine detail preservation. The algorithm consistently outperforms others in key metrics such as PSNR, SSIM, entropy, and Edge Preservation Index, making it a superior choice for medical image fusion. Despite a slight trade-off in computational efficiency compared to techniques like PCA and wavelet transform, the high-quality results justify the increased processing time, and future optimizations, such as GPU acceleration, could further improve efficiency. The fused images are not only visually superior but also diagnostically reliable, making the algorithm a valuable tool for clinical applications, particularly in areas like tumor diagnosis and surgical planning. The adaptability of the proposed method, demonstrated across multiple imaging modalities, highlights its potential to become a crucial asset in medical imaging, improving both diagnostic accuracy and clinical decision-making.

5. Conclusion

This study introduced a novel modified NSCT-based algorithm for medical image fusion, which demonstrated superior performance compared to traditional methods such as Wavelet Transform, PCA, and standard NSCT. The proposed algorithm consistently outperformed existing techniques across key metrics like PSNR, SSIM, entropy, and EPI, ensuring better noise suppression, structural information preservation, and enhanced detail and edge retention. Its versatility was showcased through a successful application to multiple modalities, including MRI, PET, MRA, CT, and SPECT imaging. The method's computational efficiency, though slightly lower than some alternatives, remains competitive and suitable for real-time medical applications. The results highlight the algorithm's potential for improving diagnostic accuracy in clinical settings, with future work focusing on extending the method to 3D medical image fusion, integrating deep learning for feature extraction, and optimizing performance for hardware acceleration to enable broader real-time application. While the algorithm excels in medical image fusion, it may require fine-tuning for other multimodal image fusion tasks, such as satellite or hyperspectral images. Future work will explore these applications while further optimizing computational efficiency.

Conflict of interest: The author declares no conflict of interest.

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