



## Bendlet-Based Medical Image Fusion Using Modified Spatial Frequency and Contrast Visibility

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**Abstract:** Multimodal medical image fusion combines complementary anatomical and functional information from different imaging modalities into a single image to support clearer visualization and more informed clinical interpretation. Conventional fusion methods may introduce blurring, reduce contrast, or lose important edge and texture information, particularly when curved anatomical boundaries are not represented effectively. This study proposes a Bendlet-based medical image fusion framework that integrates the Bendlet Transform with Contrast Visibility (CV) and Modified Spatial Frequency (MSF) fusion rules. The source images are first decomposed into low- and high-frequency subbands using four multiscale levels and directional subbands of [8, 8, 16, 16]. A bending parameter of 0.5 is used to represent curved image structures, and the transformed coefficients are processed in non-overlapping  $32 \times 32$  blocks. The low-frequency coefficients are fused using the CV rule to preserve intensity and contrast information, whereas the high-frequency coefficients are fused using the MSF criterion to retain edges, textures, and local structural details. The final fused image is reconstructed through the inverse Bendlet Transform. The proposed method is evaluated on five medical-image databases using qualitative inspection and objective fusion metrics, including entropy, standard deviation, mutual information, spatial frequency, fusion symmetry, structural similarity, and edge-based quality measures. The reported comparisons indicate that the proposed method preserves complementary information and produces visually clearer fused images than the comparison techniques considered in the study. These findings suggest that Bendlet-based decomposition combined with frequency-specific fusion rules is a promising approach for multimodal medical image fusion, although broader clinical validation and statistical analysis are required before diagnostic use.

**Keywords:** Bendlet Transform, Contrast Visibility, Entropy, Medical Image Fusion, Modified Spatial Frequency.

### 1. Introduction

Modern healthcare and medicine heavily depend on image processing techniques, like image fusion, to combine different types of medical imaging, namely X-ray, CT, MRI, PET, and MRA scans [1]. When CT and MRI are used in tandem, significant volumes of useful diagnostic information are uncovered. Both CT and MRI scans serve their imaging purposes effectively; for example, CT scans are imperative to visualizing denser structures such as bones and implants, as well as exhibiting minimal imaging distortion, while MRI scans excel at visualizing normal and abnormal soft tissues. The creation of new algorithms that enable the extraction of comprehensive information from images has substantially boosted the breakthroughs in signal and image processing. Aims of integrating computers into diagnostic processes include improved detection, monitoring, and therapeutic strategies. Diagnostic

imaging and other techniques can be integrated to enhance analysis. Each imaging modality [2] provides its own particular value to problem-solving analysis, and integration leads to better diagnostic capability. A significant challenge in the field of medical image processing is determining the optimal way to use the data generated by the combination of different image acquisition modalities.

Below is a summary of what the literature has offered. For a complete overview of medical image fusion techniques, see [3, 4]. Pixel averaging is one of the simplest image fusion techniques [5]; however, this technique is not without its drawbacks. When the decomposition process is carried out using pyramid-based algorithms, fused images exhibit undesirable edge and blocking artifacts due to a lack of spatial and directional selectivity. A wavelet-based fusion technique is one of the ways to incorporate resolution. It utilizes the discrete wavelet transform (DWT). This allows the

storage and organization of information across a spectrum of frequencies and facilitates an accurate representation of waveforms in the time and frequency domains. While the DWT has the ability to capture high frequency information across multiple resolutions, it suffers from shift invariance, meaning minor variations in an image cause drastic changes in the DWT coefficients. In order to achieve medical image fusion, bendlets [6], a transform, are required to preserve the spatial coherence of the information.

Some images consist of distinct segments that are separated by smooth curves. Photographs depict various objects with edges defined by the interruption of spatial continuity. Medical imaging relies on the use of curves to separate the different structures comprising bones and other soft tissues. In geoscience, the differentiation of geological strata causes changes to the data samples collected. The variations that exist between different regions indicate the structure and content of an image. Having a thorough grasp of their location and geometric properties can be immensely helpful in a wide range of image processing, analysis, and comprehension tasks. Finding and describing boundary curves in piecewise smooth images is a challenging task, but directional representation techniques [7] perform exceptionally well. In comparison to regular wavelets, bendlet systems [8] can accurately identify boundaries and give details regarding their directional normal.

We present a medical image fusion method that uses the Bendlet Transform to improve fusion quality [9]. The principal contributions of the study are as follows:

- A Bendlet-based framework is developed for multimodal medical image fusion.
- The CV model is used for the low-frequency bands.
- For high-frequency bands, the MSF model is employed.

## 2. Literature Review

Medical image fusion combines complementary information from different imaging modalities. CT images provide clear visualization of bones and other dense structures, whereas MRI images provide detailed information about soft tissues. However, conventional wavelet-based methods can introduce blocking artifacts because of limited shift invariance.

This section reviews image-fusion methods in four principal categories

### 2.1 Spatial-Domain Fusion

In the spatial domain, images are combined directly at the pixel level without transformation into a

frequency-domain representation. These methods are computationally simple, require relatively little processing time, and can be suitable for real-time or resource-constrained systems. However, they may introduce spectral distortion, edge blurring, and noise. Their limited frequency-domain analysis can also reduce the preservation of low-frequency information and texture in complex medical-imaging tasks.

Li *et al.* [10] and Du *et al.* [11] furthered the techniques of multi-scale transformation with edge-preserving filter techniques to retain structure and improve contrast. They were the first to explore the hybrid technique of spatial-transform fusion. In the same way, Zhan [12] fused brain images using guided filtering and spatial gradient enhancement to improve brain tissue and lesion regions of complicated structures.

Substantial progress was reported between 2018 and 2023. Liu *et al.* [13], Na *et al.* [14], Saboori *et al.* [15], and Pei *et al.* [16] used wavelet-based, multiresolution, and guided-filtering methods to preserve image features and reduce distortion. These methods were applied to PET–MRI and CT–MRI fusion and to brain-imaging applications. Tan *et al.* [17], Chen *et al.* [18], and Sale *et al.* [19] developed less complex methods intended for efficient execution. More recently, Li *et al.* [20] proposed a spatial-fusion framework incorporating bilateral filtering, least-squares processing, and saliency detection.

There is a clear trend and move toward hybrid systems, adaptive spatial analysis and multi-scale fusion within the spatial domain. These methods have improved the reliability and efficacy of fusion systems for clinical applications such as lesion detection and radiotherapy planning as well as in neuroimaging diagnosis.

### 2.2 Transform-Domain Fusion

Transform- or frequency-domain methods can address several limitations of direct spatial-domain fusion. Their principal advantage is the extraction and preservation of spatial, spectral, and textural information during fusion.

Some of the early attempts to address the challenges of shift variance and reduced directionality in the real-valued wavelet transform can be found in Singh and Khare *et al.* [21], which is based on the Dual-Tree Complex Wavelet Transform (DTCWT). The DTCWT retains direction and phase to a greater extent and thus has better fusion quality. During the same time, Vakaimalar *et al.* [22] produced a good quality fused image using discrete cosine transform, and Ganasala and Prasad presented [23] a multimodal image fusion framework combining CT and MRI images using the stationary wavelet transform. Meenu *et al.* [24] focused on intuitionistic fuzzy set-related fusion methods to address vagueness and uncertainty in the diagnostic

visualization of soft tissues and bone structures. Their methods improved the diagnosis of soft tissue and skeletal structures.

Transformation-based fusion techniques were further advanced by Bhateja *et al.* [25] through the introduction of a wavelet and contourlet transform-based two-stage fusion framework. Edge improvement and directionality were enhanced by the Curvelet Transform along with a localized energy-based fusion technique in the work of Srivastava *et al.* [26]. Their method demonstrated effective retention of the anisotropic property and subjective improvement of the visual quality.

Xu *et al.* [27] proposed the Discrete Fractional Wavelet Transform (DFRWT) to improve the flexibility of multimodal image fusion techniques by using fractional-order parameters for adaptive image decomposition. In a similar manner, Gomathi and Kalaavathi *et al.* [28] have shown that NSCT-based methods allow for efficient multi-scale, multi-directional frequency decomposition, while retaining crucial high-frequency details. Fusion methods proposed by Li *et al.* [29] and Gupta *et al.* [30] that applied the Non-Subsampled Shearlet Transform (NSST) along with an improved fusion rule to reduce blocking and blurring artifacts by using local coefficient energy and local mean. Furthermore, Kong *et al.* [31] improved the fusion by preserving edges, textures and structural boundaries beyond others, by combining the NSST methods, median NSST methods and Framelet Transform methods along with Recursive Guided Filtering (RGF) and Domain Transform Filtering (DTF).

2.3 Deep-learning fusion methods: Deep neural networks can extract hierarchical features at multiple levels. However, efficient and interpretable architectures remain necessary. Such models are designed to improve structural preservation, semantic consistency, and the usefulness of fused images for diagnostic tasks.

### 2.3 Deep Learning Fusion Methods

Deep Neural Networks (DNNs) have shown a great potential in the extraction of deep, hierarchical and multiple levels of features; however, a lot of focus is still required for the development of efficient and architecture that is interpretable. These models are trained to improve the accuracy of disease detection and optimize the structural preservation and consistency of the fused images and the retained semantical information.

One of the first applications of the use of a CNNs for medical image fusion was reported by Liu *et al.* [32], and showed that CNN-based fusion outperformed the traditional ways of performing medical image fusion in the spatial and transform domains. Extraction of spatial, structural, and textural features with CNN architectures was also shown to be effective, however, they have been known to be data-hungry, requiring the availability of

massive, labeled, and quality data, and are known to be inefficient without careful optimization of the parameters. Liu *et al.* [33] also described the use of local filtering and clarity maps as fusion and activity levels estimation techniques to integrate high-frequency information in a fused image. Later work by Xia *et al.* [34], demonstrated a more sophisticated approach, fusing CNNs with a multiscale decomposition framework. In turn, Wang *et al.* [35] utilized Siamese CNN-based architectures and introduced the generation of 'activity-driven' weight maps, thereby producing fused images with improved structural fidelity and enhanced quality.

In response to the limitations of batch processing, real-time multimodal image fusion CNN-based models were proposed by Li *et al.* [36]. These fusion models improved the methodologies in both the retention of structural and textural framework and in the efficiency of computation, thereby achieving the requirements to perform simultaneous fusion of multiple clinical images. Fan *et al.* [37] presented Fusion W-Net (FW-Net), a semantic-aware deep neural network designed for multimodal medical image fusion. By leveraging an optimized fusion strategy, the framework effectively minimizes semantic information loss while generating high-quality fused images with enhanced structural and visual fidelity, demonstrating superior performance over existing fusion approaches. A hybrid deep learning fusion paradigm was proposed by El-Shafai *et al.* [38], where CNNs and traditional image fusion methods were merged. This new paradigm combined three images and reduced redundancy while improving clarity and semantic representation of the images.

Overall, the field of medical image fusion has been enhanced by the use of deep learning approaches as they facilitate automatic learning of features, have the ability to adaptively fuse information, and can preserve structural as well as semantic information more effectively. These approaches are almost certainly capable of having a much wider impact on more sophisticated clinical applications such as disease diagnosis, lesion identification, as well as multimodal medical image analysis.

### 2.4 Hybrid-Domain Fusion

Hybrid fusion methods combine complementary advantages of spatial-domain, transform-domain, and learning-based approaches. Examples include multiscale decomposition with the nonsubsampled contourlet transform and adaptive fusion using neural networks.

One of the original hybrid fusion methods was proposed by Xia *et al.* [39], where the Nonsubsampled Contourlet Transform (NSCT) and the Dual-Tree Complex Wavelet Transform (DTCWT) were integrated. This framework also included the PCNN to synthesise

the final fused images. This integrated transformation method was a step forward to address concerns of image noise, feature matching, and retaining characteristics of the image.

The hybrid fusion methods were advanced by Bhateja *et al.* [40], who proposed a framework for the combination of shearlet transforms and NSCT to merge PET/SPECT, MRI, and CT imaging. This also integrated contrast enhancement along with PCA in a weighted manner to maintain consistency of multi-spectral imaging and structural fidelity. Du *et al.* [41] suggested specialized fusion approaches that focused on integrating MRI and PET imaging, each of which utilized dimension reduction with edge-based weighting, to improve the accuracy of the fusion and enhance the features that were represented.

Kaur *et al.* [42] paired Adaptive Neuro-Fuzzy Inference Systems (ANFIS) with cross-bilateral filtering to obtain better entropy scores. This also demonstrated the possibility of volumetric fusion in future applications of neuroimaging. In the same vein, Polinati *et al.* [43] and Li *et al.* [44] proposed the use of hybrid frameworks and the incorporation of Variational Mode Decomposition (VMD) paired with local energy gradient analysis and bilateral filtering to augment image clarity with reduced degradation of luminance. Zhu *et al.* [45] targeted the improvement of NSST-DTCWT-based models of image fusion and texture control with the preservation of structural consistency. Kalamkar and Geetha *et al.* [46] used transfer learning based on Discrete Wavelet Transform (DWT) and demonstrated increased Structural Similarity Index (SSIM) and improved image quality.

Significant improvements have also been made by Zhou *et al.* [47], who resolved the issues of loss of image details and brightness degradation by incorporating the Non-Subsampled Shearlet Transform (NSST) and Improved Structure Tensor (IST) decomposition. This approach provided better image contrast and facilitated the clear identification of smoothing regions, edges, and corner structures. Dinh *et al.* [48] introduced two complementary hybrid models for image fusion based on three-scale decomposition and local energy driven fusion with the goal of overcoming the issues of low contrast and edge degradation. Most notably, the three-scale frequency decomposition framework with the use of SSIM-optimized feature blending proposed by Zhao *et al.* [49] took a major step in improving the MRI-PET image fusion in the context of brain tumor analysis.

In general, hybrid-domain fusion methods have the most promising ability to retain and capture the fine structural details and texture-infused contextual semantics because of the unique ways they combine various methods. Their flexibility and enhanced fusion precision can support sophisticated medical imaging tasks. This is especially true for the analysis of

multimodal brain images, tumor detection, and clinical decision aid systems.

In many images, regions may be delineated by boundaries that exhibit both smooth and irregular characteristics. Such boundaries occur as a result of spatial occlusions and the presence of multiple objects within the image. Curved boundaries are especially significant in medical imaging as they assist in differentiating bones, tissues, and other structures. The presence of boundaries and other regional characteristics in an image is significant in computer vision and image analysis, and image interpretation. Therefore, the identification of the position of these boundaries and the curves and their geometric characteristics is very important in the understanding of image structure and in the formulation of image content. The detection of these features is very useful in image processing, segmentation, and the recognition of objects in images.

Although there have been major advancements in image analysis, the extraction of objects containing complex, curved boundaries continues to be a difficult problem for many algorithms. To surmount these limitations, Bendlet transform methods have been developed. Bendlets are particularly useful for describing features that are curved and directional, and for the geometric description of images. In medical image fusion, Bendlets are very useful for maintaining and describing the directionality and structure of fused images and for diminishing redundancy and noise. This is very useful in clinical imaging as it helps in the accurate localization of structures, both normal and pathological, for diagnosis.

To enhance the improvement of fusion, a hybrid medical image fusion framework was developed through the integration of Bendlet transform, MSF, and CV methods. The combination of these methods significantly improves the preservation of structure, localization of features, and the quality of images, making the framework adequate for advanced applications in medical imaging.

### 3. Approaches

Bendlets are a mathematical structure frequently utilized in the field of image processing. Specifically, they are helpful in image fusion. This technique is essential in medical imaging, as it enhances the quality of the produced image along with its diagnostic value. Bendlets are derived from wavelets, which are mathematical functions used for the analysis and processing of signals and images. Wavelets provide an exceptional capacity to collect signals at various sizes and resolutions, making them very helpful for a diverse array of image processing applications. Bendlets are a distinct kind of wavelet transform that incorporates directional information into the breakdown of an image.

Bendlets, unlike traditional wavelets, are designed with the particular purpose of identifying directional attributes in an image, such as edges and textures.

Let  $\Psi \in L^2(R^2)$ ,  $l \in N$ ,  $\alpha > 0$ . Using the representation  $\pi^{(l,\alpha)}$  the  $l$ -th order  $\alpha$ -shearlet transform [50] is defined as:

$$ST_{\Psi}^{(l,\alpha)} = \left\{ \pi^{(l,\alpha)}(a, r, t) \Psi \mid (a, r, t) \in T^{(l,\alpha)} \right\} \quad (1)$$

Where 'a' is scale parameter, 't' is translation,  $r=(S,B)$  such that S is shearing, B is bending of the functions  $\pi^{(l,\alpha)}(a, r, t) \Psi$ . The decomposition procedure employs a bendlet generator  $\psi$  to represent the image in terms of multiple scales, orientations, and curvature-based features. The associated continuous  $l$ -th order  $\alpha$ -shearlet transform of a function  $f \in L^2(R^2)$  is the function given by

### 3.1 Bendlet Transform

Bendlets are mathematical representations used in image processing, including image fusion. They extend wavelet and shearlet concepts by incorporating directional and curvature information, which can help represent edges, textures, and curved anatomical structures. The second order shearlet transform when  $l=2$ , since bending is the most characteristic property we call the associated transform a bendlet transform.

For any function  $f \in L^2(R^2)$ , the bendlet transform (BT) with respect to the square integral analyzing function  $\Psi \in L^2(R^2)$  is denoted mathematically as:

$$BT_{\Psi}^{\alpha}(f)(a, s, b, t) = \langle f, \Psi_{a,s,b,t} \rangle \quad (3)$$

Where,  $\Psi_{a,s,b,t} = \pi^{(2,\alpha)}(a, (s,b), t) \Psi$ ,  $a > 0$ ,  $\alpha$  is a scaling factor ranging  $0 \leq \alpha < \infty$  which is defined as:

$$A_{a,\alpha} = \begin{pmatrix} a & 0 \\ 0 & a^{\alpha} \end{pmatrix} \quad (4)$$

$\alpha=0$  means directional scaling,  $\alpha=1$  means isotropic scaling,  $\alpha=0.5$  means parabolic scaling.

Reconstruction is the reverse operation in which the bendlet coefficients are transformed back into the spatial domain to recover the original signal.

The original signal 'f' can be recovered from its bendlet coefficients  $BT_{\Psi}^{\alpha} f$  through the following reconstruction expression:

$$f(x) = \int_{R_+} \int_{R} \int_{R} \int_{R^2} BT_{\Psi}^{\alpha} f(a, s, b, t) \Psi_{a,s,b,t}(x) da ds db dt \quad (5)$$

The bendlet function uses directional filter banks to extract information along certain orientations. After the image is decomposed into bendlet coefficients at various scales and orientations, fusion algorithms can be used to combine information from multiple images or modalities, yielding a fused image with important directional features while improving overall quality and informativeness. Bendlets lay the groundwork for incorporating adaptable directional frameworks into medical image fusion, which could enhance both diagnosis and treatment. In traditional directional transforms, adaptivity is usually associated with anisotropic scaling and  $\alpha$ -scaling, and with transformations of the position/orientation of transform elements. Bendlets differ, as they introduce bending as an additional degree of freedom to the elements of the transform. In figure 1 [51], the transform elements are called bendlets. The added degree of freedom in the bendlets adapts them better to the local curvature of the contour, resulting in improved characterization of curvature and features. Because shearing is linearly dependent and bending is quadratically dependent on the space, bendlets are viewed as a second order shearlet system.

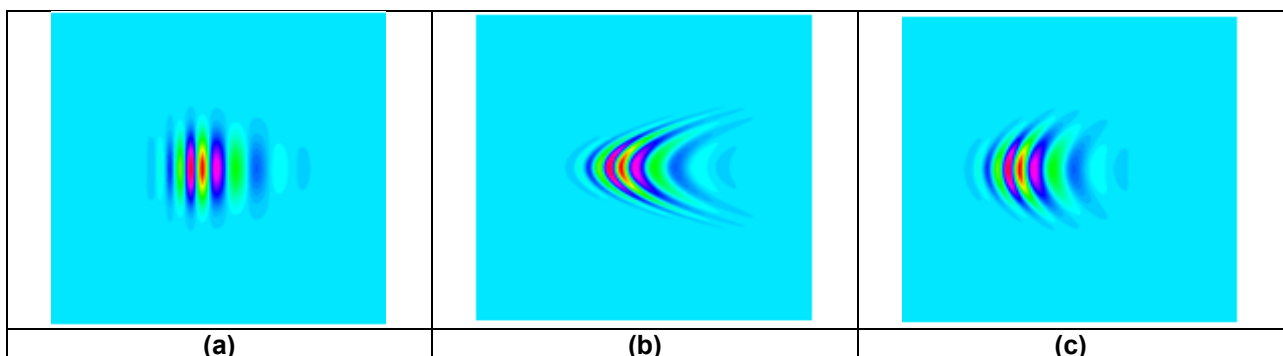


**Figure 1.** (a) Classical shearlet with no bending (b) Bendlet with bending in spatial domain of order 1 (c) Bendlet with bending in spatial domain of order 2.

Additionally, bendlets are a particular form of the higher-order shearlet systems, which offer better adaptivity and directional representation for complex structures in the domain of images. In comparison with shearlets, the bendlet transform more effectively retains texture and edge information in medical images such as MRI and CT scans, resulting in improved PSNR and SSIM performance.

### 3.2 Fusion at Low Frequency using CV

Contrast Visibility [52] measures the distance of individual block pixels from the block's mean value, it is a more suitable metric to utilize than variances and averages. The accuracy of the right portions is hence its primary concern. The use of (6) determines whether the image block is visible.

$$CV = \frac{1}{m \times n} \sum_{(i,j) \in B_k} \frac{|I(i,j) - \mu_k|}{\mu_k} \quad (6)$$

Here,  $I$  is input image,  $\mu_k$  is mean, and  $m \times n$ , the size of the block  $B_k$ .

### 3.3 Fusion at High Frequency using MSF

Modified spatial frequency [53] captures the overall level of activity in an image, along with its nuanced variations and changing textures. The resolution of the image improves as the spatial frequency increases. By utilizing equation (7), the enhanced spatial frequency of the high frequency subbands of the two input images can be determined.

$$MSF = \sqrt{RF^2 + CF^2 + DF^2} \quad (7)$$

where,

$$RF = \text{Row Frequency} = \sqrt{\frac{1}{mn} \sum_{i=1}^m \sum_{j=2}^n [F(i,j) - F(i,j-1)]^2} \quad (8)$$

$$CF = \text{Column Frequency} = \sqrt{\frac{1}{mn} \sum_{i=2}^m \sum_{j=1}^n [F(i,j) - F(i-1,j)]^2} \quad (9)$$

and,

$$DF = \text{Diagonal Frequency} = R + S \quad (10)$$

where,

$$R = \sqrt{\frac{1}{mn} \sum_{i=2}^m \sum_{j=2}^n [F(i,j) - F(i-1,j-1)]^2} \quad (11)$$

$$S = \sqrt{\frac{1}{mn} \sum_{i=2}^m \sum_{j=2}^n [F(i-1,j) - F(i,j-1)]^2} \quad (12)$$

## 4. Proposed Technique

This section describes the proposed Bendlet-based approach for multimodal medical image fusion.

### 4.1 System Model

The proposed algorithm's steps are below:

- (1) Observe the images provided as input.
- (2) Perform Bendlet decomposition for the two input source images  $X$  and  $Y$  to get LFSs and HFSs.
- (3) The bendlet decomposition was conducted utilizing four multiscale levels with directional subbands of [8, 8, 16, 16].
- (4) A bending parameter of 0.5 was used to appropriately capture the curves the image structures.
- (5) The transformed coefficients were grouped in a non-overlapping manner into blocks of size  $32 \times 32$  for local feature extraction.
- (6) For the separated LFSs blocks, the Contrast Visibility (CV) measure is calculated, and the block with the larger feature value was selected for fusion.

Contrast visibility is applied on two decomposed LFSs of two images to form fused LFS<sub>F</sub>.

Equation (13) demonstrates the fusion of the LFSs coefficients using the updated contrast visibility fusion technique, resulting in the creation of the fused low frequency subband (LFS<sub>F</sub>) image.

$$LFS_F = \begin{cases} LFS_i^X & \text{if } CV_i^X > CV_i^Y \\ LFS_i^Y & \text{otherwise} \end{cases} \quad (13)$$

LFS<sub>F</sub> is the abbreviation for the combined LFS image, while  $CV_i^X$  and  $CV_i^Y$  are the abbreviations for the contrast visibility of the  $i$ th region in the  $X$  and  $Y$  images, respectively.

- (7) For the separated HFSs blocks, the Modified Spatial Frequency (MSF) measure is calculated, and the block with the larger feature value was selected for fusion.

Modified spatial frequency is applied on two decomposed HFSs of two images to form fused HFS<sub>F</sub>. The modified spatial frequency fusion algorithm (Equation 14) is utilized to construct the fused image in the low frequency subband by fusing the coefficients.

- (8) The final fused image is obtained by applying an inverse bendlet transform to the fused low-frequency subband (LFS<sub>F</sub>) and fused high-frequency subband (HFS<sub>F</sub>).

### 4.2 Working and Architecture

The structure below shows the proposed algorithm for decomposition and fusing subbands using bendlet transform. The proposed method is illustrated in Figure 2.

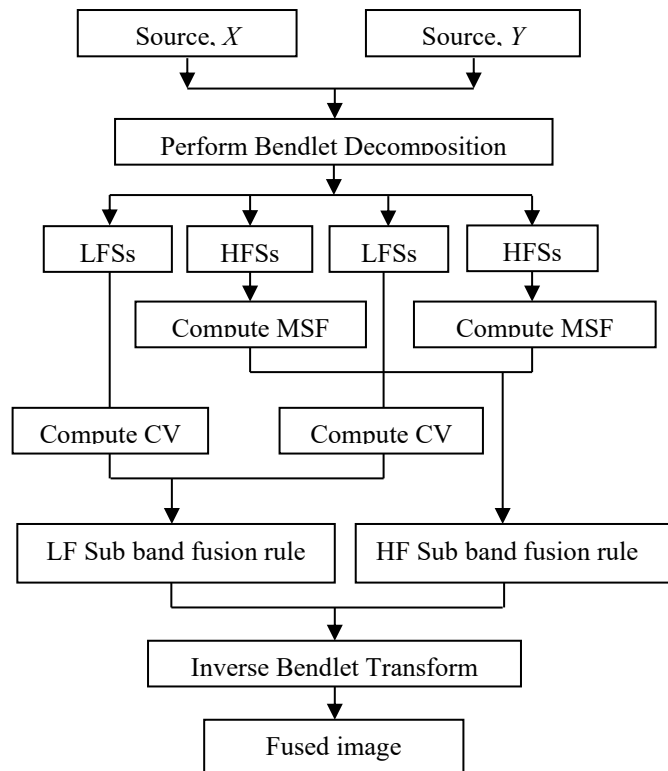


**Figure 2.** Representation of the process flow.

The proposed algorithm for image fusion involves five steps: low-frequency fusion, bendlet reconstruction, high-frequency fusion and bendlet decomposition. For this algorithm, the input image comes from both a CT and an MRI and the image is decomposed into low and high frequency subbands using bendlet decomposition. In the proposed algorithm, the low-frequency subbands are fused using the MSF fusion rule, and the high-frequency subbands are fused using the contrast visibility rule. Once the pairs of images are fused, a reverse bendlet transform is performed to obtain the final fused image.

## 5. Results

In this section we test the proposed algorithm on different examples of medical image datasets. In all cases assumed source images are well registered.

### 5.1 Objective Evaluation

Fused images are analyzed using both subjective and objective measures [54], which include standard deviation (SD), average gradient (AG), entropy, fusion symmetry (FS), correlation coefficient (CC), spatial frequency (SF), edge strength, and computational time (CT).

#### 5.1.1 Standard Deviation (SD)

It measures fused image contrast. High standard deviation indicates a high-contrast fused image. It is given by:

$$SD = \sqrt{\sum_{i=0}^L (i - \bar{i})^2 h_{I_f}(i)}, \quad \bar{i} = \frac{\sum_{i=0}^L i h_{I_f}(i)}{\sum_{i=0}^L h_{I_f}(i)} \quad (14)$$

#### 5.1.2 Average Gradient (AG)

It is a measurement of the degree of sharpness and clarity, and it is provided by

$$AG = \frac{\sum_{m=1}^M \sum_{n=1}^N \left( (f(i,j) - f(i+1,j))^2 + (f(i,j) - f(i,j+1))^2 \right)^{1/2}}{MN} \quad (15)$$

#### 5.1.3 Entropy (E)

A fused image's average information content is gauged using entropy. What it means is:

$$E = -\sum_{i=0}^L h_{I_f}(i) \log_2 h_{I_f}(i), \quad (16)$$

Where L indicates the number of frequency bins in the histogram and  $h_{I_f}(i)$  is the fused image's normalised histogram.

#### 5.1.4 Fusion Symmetry (FS)

Information symmetry, also known as fusion symmetry, measures how symmetric the fused image is in relation to the source images. It is given by

$$FS = 2 - \left| \frac{MI_{ZX}}{MI} - 0.5 \right| \quad (17)$$

Where MI stands for Mutual Information and is given by:

$$MI = I_{Z,X}(z, x) + I_{Z,Y}(z, y) \quad (18)$$

$$I_{Z,X}(z, x) = \sum_{z,x} P_{Z,X}(z, x) \log \frac{P_{Z,X}(z, x)}{P_Z(z)P_X(x)} \quad (19)$$

$$I_{Z,Y}(z, y) = \sum_{z,y} P_{Z,Y}(z, y) \log \frac{P_{Z,Y}(z, y)}{P_Z(z)P_Y(y)} \quad (20)$$

### 5.1.5 Correlation Coefficient (CC)

This shows the correlation between the reference and fused image. The ideal value is one when the reference and fused images are exactly alike and it will be less than one when the dissimilarity increases. It is defined as:

$$CC = \frac{2C_{rf}}{C_r + C_f} \quad (21)$$

Where  $C_r = \sum_{i=1}^M \sum_{j=1}^N I_r(i, j)^2$ ,  $C_f = \sum_{i=1}^M \sum_{j=1}^N I_f(i, j)^2$  and  $C_{rf} = \sum_{i=1}^M \sum_{j=1}^N I_r(i, j) I_f(i, j)$

### 5.1.6 Spatial Frequency (SF)

It quantifies a fused image's activity and represents contrasts and surface variations. The Spatial Frequency is given as:

$$SF = \sqrt{(RF)^2 + (CF)^2} \quad (22)$$

Here, row frequency and column frequency are used to determine RF and CF, respectively.

$$RF = \sqrt{\frac{1}{MN} \sum_{x=1}^M \sum_{y=2}^N [I_f(x, y) - I_f(x, y-1)]^2}$$

$$CF = \sqrt{\frac{1}{MN} \sum_{x=2}^M \sum_{y=1}^N [I_f(x, y) - I_f(x-1, y)]^2} \quad (23)$$

### 5.1.7 Edge-Based Image-Fusion Metric

This metric measures the amount of edge information transferred from the source images to the fused image.

$$Q^{I_1 I_2 / F}(n, m) = \frac{\sum_{m=1}^M \sum_{n=1}^N Q^{I_1 F}(n, m) W^{I_1}(n, m) + Q^{I_2 F}(n, m) W^{I_2}(n, m)}{\sum_{m=1}^M \sum_{n=1}^N (W^{I_1}(n, m) + W^{I_2}(n, m))} \quad (24)$$

Where the accompanying weights  $W^{I_1}(n, m) = [g_{I_1}(n, m)]^L$ ,  $W^{I_2}(n, m) = [g_{I_2}(n, m)]^L$  are elements of edge strength.  $L$  is considered as constant

and is equal to 1. The range of  $Q^{I_1 I_2 / F}$  is  $0 \leq Q^{I_1 I_2 / F} \leq 1$ . A value of 0 corresponds to the complete loss of edge information, at location  $(n, m)$ .

## 5.2 Experimental Dataset

### 5.2.1 Dataset Provenance

The experiments were conducted using publicly available multimodal medical image datasets (Harvard Whole Brain Atlas, Whole Brain Atlas, Image Fusion Benchmark, etc.) [55, 56] obtained from widely used benchmark repositories. The dataset consists of registered image pairs acquired from different imaging modalities, including Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), and Single Photon Emission Computed Tomography (SPECT). These datasets have been extensively used in previous medical image fusion studies to evaluate fusion algorithms.

### Case Selection

Only image pairs satisfying the following criteria were included in the experiments:

- Registered image pairs are available for both modalities.
- Images represent identical anatomical regions.
- Images are free from severe motion artifacts.
- Images have complete modality information.

### Image Registration

Since the benchmark datasets provide spatially aligned image pairs, no additional image-registration procedure was performed. All image pairs were verified for proper anatomical alignment before fusion.

### Preprocessing

Before fusion, the following preprocessing operations were performed:

- Image resizing to a common spatial resolution.
- Intensity normalization to the range [0, 1].
- Removal of background artifacts.

### Image Dimensions

All images were resized to  $256 \times 256$  pixels prior to fusion to maintain uniformity across all experiments.

### Modality Pairings

The proposed method was evaluated using the following multimodal image combinations:

- CT–MRI
- MR–MRA
- MRI–PET

- MRI–SPECT
- X-ray–VA

### 5.3 Discussion

CT and MRI images [55, 56] shown in figure 3 complement each other and occupy similar fields, providing soft-tissue information from MRI and CT of bone and hard tissues. By combining these two images, one can obtain maximum information, which facilitates better diagnosis of pathological conditions. Comparison with images generated by other methods such as simple average [5], DCT [22], RWT [23], Fuzzy transform [24]

and NSST [30] shows that the method presented in section 3(h) has a better image quality having better brightness and contrast. The experiments were conducted using the MATLAB software [57]. In this case, we paired chest CT and MR images. Based on Figure 3, our fused images (Figure 3h) convey more information regarding hard and soft tissue than existing methods (Figure 3c-h). The images produced by our method (Figure 3n) show better luminance, contrast, and visibility. Figure 3i-n show the results from existing methods. An objective comparison of our Bendlet transform method with other available methods in the literature is shown in Table 1.

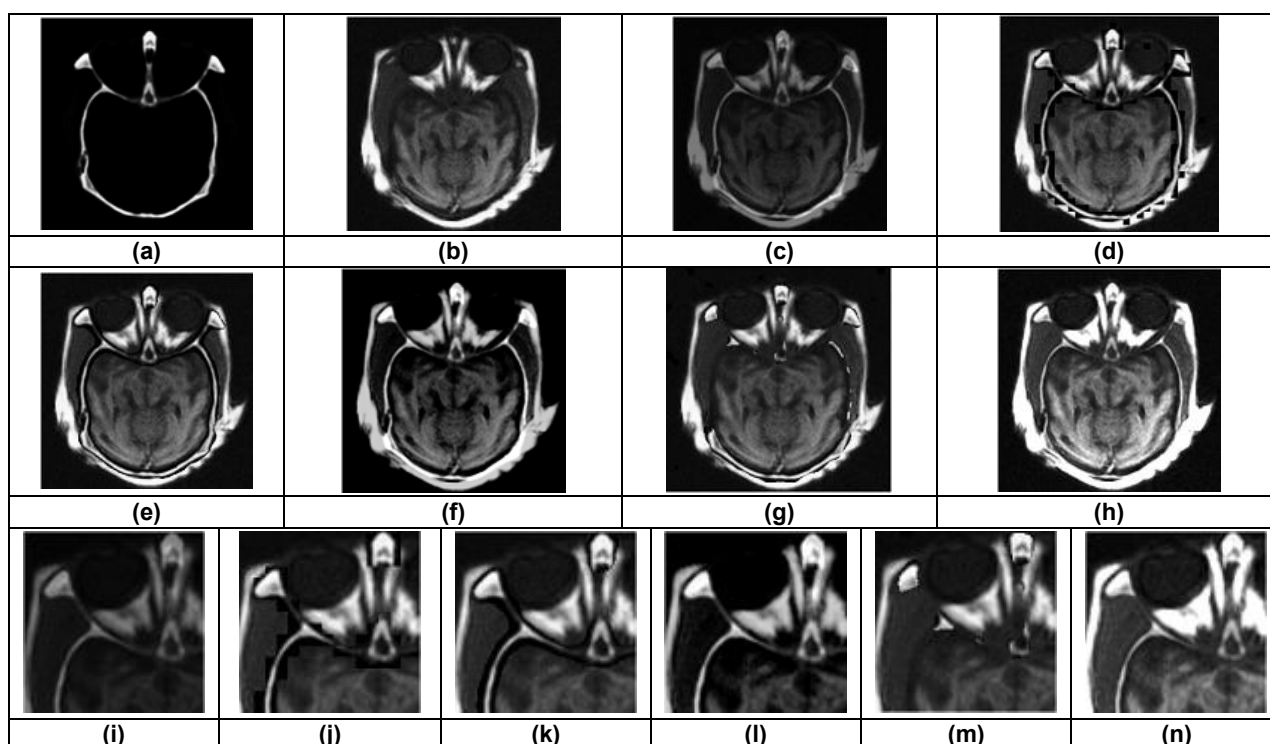


**Figure 3.** Results of Fusion for CT and MRI Images (a) CT image (b) MRI image (c) Simple average (d) DCT (e) RWT (f) Fuzzy transform (g) NSST (h) The result achieved by the proposed method (i),(j),(k),(l),(m),(n) are magnified results of (c,d,e,f,g,h,).

**Table 1.** Objective Evaluation of Spherical fuzzy set and other methods for figure 3.

| Fusion method        | SD<br>(pixel intensity) | AG<br>(change in intensity/pixel) | Entropy<br>(bits/pixel) | FS     | CC     | SF<br>(cycles/millimeter) | $Q^{AB/F}$ | CT<br>(seconds) |
|----------------------|-------------------------|-----------------------------------|-------------------------|--------|--------|---------------------------|------------|-----------------|
| Simple average [5]   | 40.0639                 | 9.5039                            | 6.0026                  | 1.6743 | 0.6739 | 24.3323                   | 0.5683     | 2.3             |
| DCT [22]             | 63.0916                 | 15.6986                           | 6.8008                  | 1.6659 | 0.6296 | 32.2774                   | 0.8301     | 3.08            |
| RWT [23]             | 63.0155                 | 15.9896                           | 6.8189                  | 1.6587 | 0.6332 | 32.4351                   | 0.8661     | 7.25            |
| Fuzzy transform [24] | 61.8750                 | 14.4624                           | 6.7823                  | 1.6346 | 0.6002 | 31.5100                   | 0.7324     | 2.76            |
| NSST [30]            | 59.4228                 | 12.5549                           | 6.5026                  | 1.6444 | 0.6553 | 25.1702                   | 0.7451     | 3.1             |
| Proposed method      | 70.2741                 | 14.7025                           | 7.3216                  | 1.6795 | 0.8021 | 31.0097                   | 0.4465     | 2.64            |

The resulting fused image with our Bendlet Transform method achieves an average information content entropy of 7.3216 bits per pixel, a fusion symmetry of 1.6795, a correlation coefficient of 0.8021, and takes around 2.64 seconds.

The pair of medical images given in the second example of Figure 4 consists of T1-weighted MR and MRA images. T1-weighted MR imaging provides information about soft tissues, but does not reveal any abnormalities in the image. MRA imaging provides low spatial resolution, and although structures can be identified, it does not have the soft tissue detail. Thus,

the combination of the two images would provide integrated information and could be used to enhance medical imaging. In Figure 4(h), the result of our method is presented, showing soft tissues with high resolution and capturing abnormality lesions. The proposed method identifies local elements with more clarity than the advanced techniques shown in Figures 4(i-n). Table 2 contains the objective way to evaluate the proposed Bendlet transform method in relation to the other imaging techniques. The dimensions of the fused image is expressed in 86.8 pixels while the symmetry of the fusion and the time of the fusion are 1.937 and 2.15 seconds respectively.

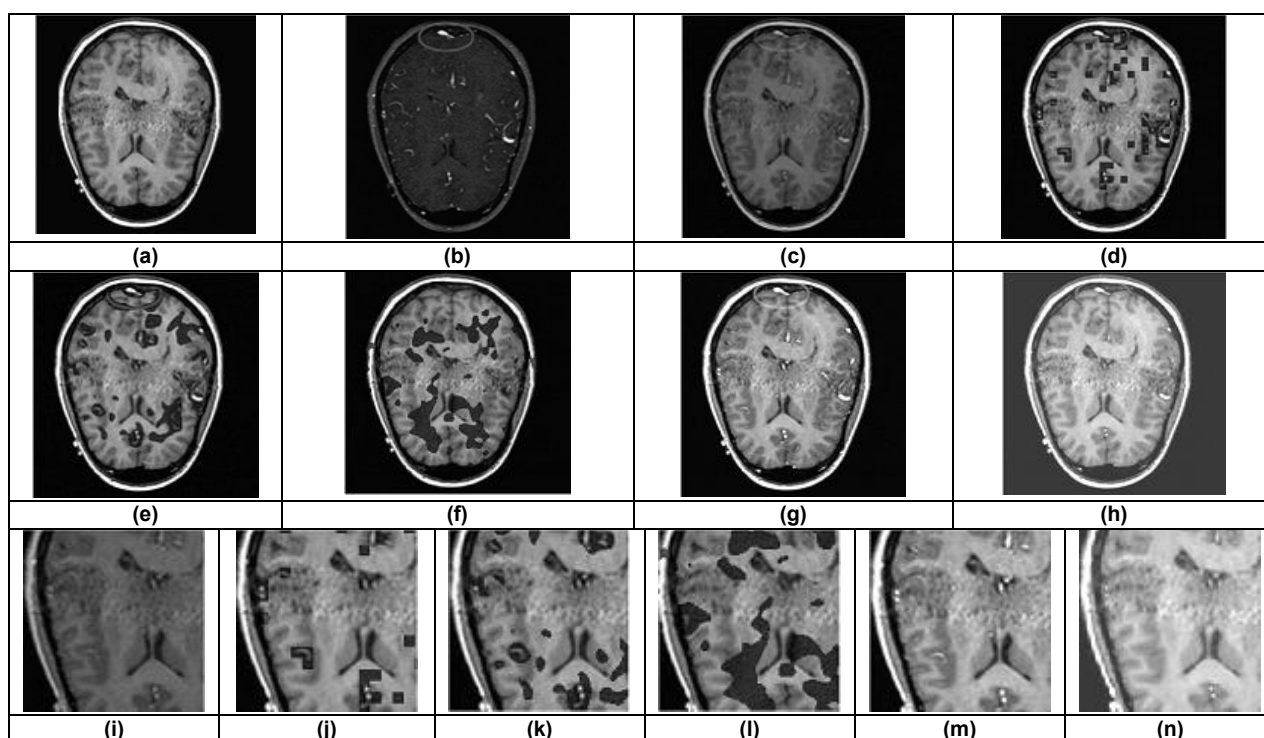


**Figure 4.** Results of Fusion for T1-weighted MR and MRA images (a) T1-weighted MR image (b) MRA image (c) Simple average (d) DCT (e) RWT (f) Fuzzy transform (g) NSST (h) The result achieved by the proposed method (i),(j),(k),(l),(m),(n) are magnified results of (c,d,e,f,g,h).

**Table 2.** Objective Evaluation of Spherical fuzzy set and other methods for figure 4.

| Fusion method        | SD (pixel intensity) | AG (change in intensity/pixel) | Entropy (bits/pixel) | FS     | CC     | SF (cycles/millimeter) | $Q^{AB/F}$ | CT (seconds) |
|----------------------|----------------------|--------------------------------|----------------------|--------|--------|------------------------|------------|--------------|
| Simple average [5]   | 47.0377              | 11.1592                        | 5.6099               | 1.9239 | 0.9966 | 26.0965                | 0.6206     | 2.04         |
| DCT [22]             | 67.9085              | 16.5856                        | 6.0732               | 1.8744 | 0.9676 | 32.9272                | 0.7565     | 3.65         |
| RWT [23]             | 67.0596              | 17.4841                        | 6.1962               | 1.9026 | 0.9469 | 33.8293                | 0.7469     | 5.07         |
| Fuzzy transform [24] | 64.6340              | 16.7764                        | 6.0653               | 1.8983 | 0.9240 | 33.5737                | 0.7042     | 2.96         |
| NSST [30]            | 64.9423              | 13.2701                        | 5.7035               | 1.8879 | 1      | 26.6297                | 0.7165     | 2.48         |
| Proposed method      | 86.8                 | 14.2087                        | 5.7424               | 1.937  | 0.6611 | 33.2646                | 0.5127     | 2.15         |

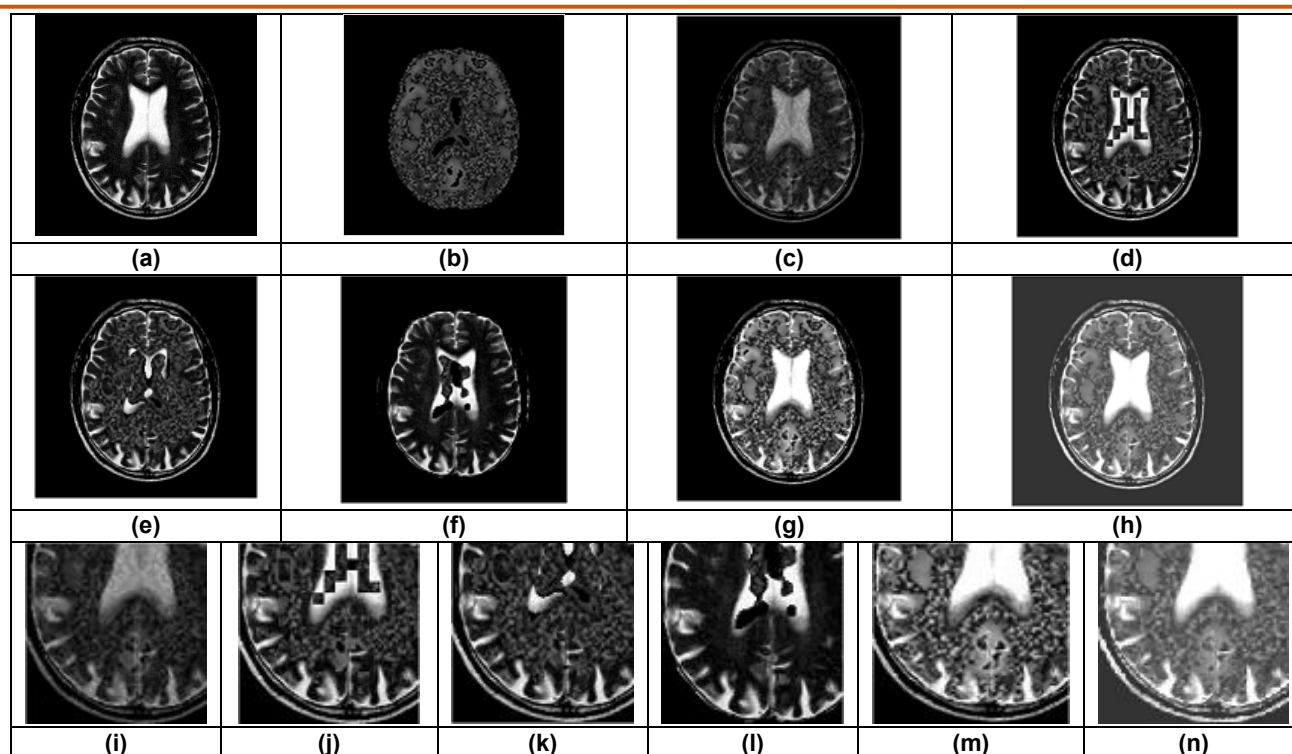


**Figure 5.** Results of Fusion for MRI and PET images (a) MRI image (b) PET image (c) Simple average (d) DCT (e) RWT (f) Fuzzy transform (g) NSST's IFS (h) The result achieved by the proposed method (i),(j),(k),(l),(m),(n) are magnified results of (c,d,e,f,g,h).

**Table 3.** Objective Evaluation of Spherical fuzzy set and other methods for figure 5.

| Fusion method        | SD (pixel intensity) | AG (change in intensity/pixel) | Entropy (bits/pixel) | FS     | CC     | SF (cycles /millimeter) | $Q^{AB/F}$ | CT (seconds) |
|----------------------|----------------------|--------------------------------|----------------------|--------|--------|-------------------------|------------|--------------|
| Simple average [5]   | 46.5168              | 11.4263                        | 3.9564               | 1.9218 | 0.8506 | 35.3043                 | 0.6189     | 2.09         |
| DCT [22]             | 58.4087              | 18.4876                        | 4.1104               | 1.9020 | 0.7875 | 44.3493                 | 0.7651     | 3.25         |
| RWT [23]             | 53.7680              | 18.0915                        | 4.0536               | 1.9173 | 0.7875 | 43.6613                 | 0.7611     | 4.94         |
| Fuzzy transform [24] | 55.0958              | 13.4784                        | 3.5434               | 1.9417 | 0.7897 | 40.1983                 | 0.5979     | 2.89         |
| NSST [30]            | 58.6045              | 15.6551                        | 4.3163               | 1.9236 | 0.8301 | 37.8728                 | 0.7483     | 2.97         |
| Proposed method      | 92.6079              | 19.3707                        | 4.0746               | 1.9339 | 0.6529 | 45.2168                 | 0.6397     | 2.56         |

The third example of medical images from the Harvard Website [www.med.harvard.edu](http://www.med.harvard.edu) consists of MRI and PET images, as shown in Figure 5. MRI provides an image of the tissue, while PET, or positron emission tomography, provides a functional image of the tissue, but with a lower than desirable resolution. Together, these modalities provide a functional image of the tissue with a better resolution than either modality in isolation. Figure 5(h) shows the fused images and provides additional information on the tissue as well as an estimate of the size of the tissue and the disease. The results of the suggested method are presented in Figure 5(n) using a zoomed-in view. An objective assessment of the Bendlet transform method and other methods found in the literature are shown in Table 3. The Bendlet

transform method produces a fused image with a pixel intensity that reaches 92.6079, a mean gradient of 19.3707 changes of intensity per pixel, a measure of spatial frequency of 45.2168 cycles per millimeter, and a fusion process that takes 2.56 seconds. The Harvard University website ([www.med.harvard.edu](http://www.med.harvard.edu)) provides the fourth medical image pair-4, which includes MRI and SPECT images, as shown in figure 6.

MRI gives us knowledge about the structure, or anatomy, of the brain, while SPECT gives us knowledge about its function. By overlaying MRI and SPECT scans, we can produce a single image that captures the structure and functional activity of the brain. Figure 6(h) displays the fused image for the provided method, giving

a more detailed description of the tumor, which assists with diagnosis. Figure 6(n) captures the enhanced image output with the provided method. Table 4 presents an objective comparison of the proposed Bendlet transform with other methods in the literature.

Pertaining to fused images, the proposed method yields an average gradient of 28.4437 change in intensity/pixel, a maximum standard deviation of 50.0227 pixel intensity, a spatial frequency of 47.6598 cycles per millimeter, and a computation time of 3.47 seconds.

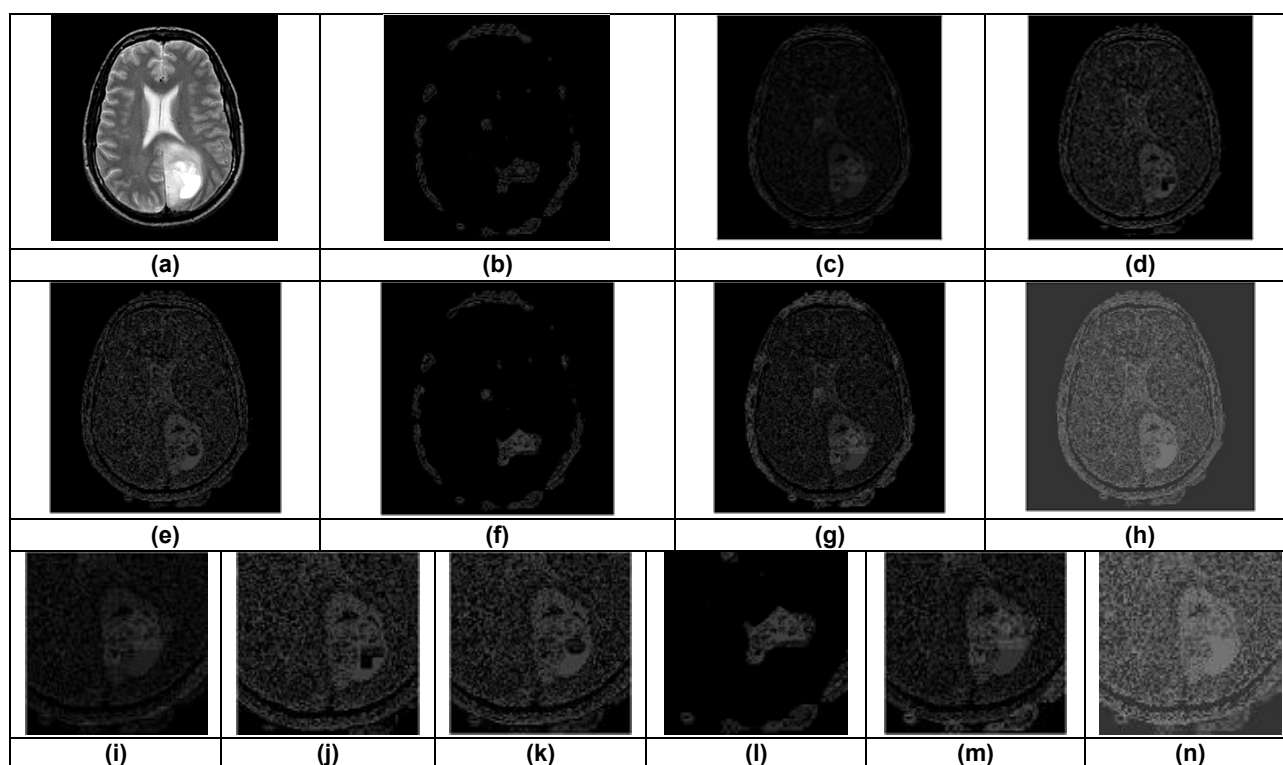


**Figure 6.** Results of Fusion for MRI and SPECT images (a) MRI image (b) SPECT image (c) Simple average (d) DCT (e) RWT (f) Fuzzy transform (g) NSST (h) The result achieved by the proposed method (i),(j),(k),(l),(m),(n) are magnified results of (c,d,e,f,g,h).

**Table 4.** Objective Evaluation of Spherical fuzzy set and other methods for figure 6.

| Fusion method        | SD<br>(pixel intensity) | AG<br>(change in intensity/pixel) | Entropy<br>(bits/pixel) | FS     | CC     | SF<br>(cycles/<br>millimeter) | $Q^{AB/F}$ | CT<br>(seconds) |
|----------------------|-------------------------|-----------------------------------|-------------------------|--------|--------|-------------------------------|------------|-----------------|
| Simple average [5]   | 32.3987                 | 10.6819                           | 3.7728                  | 1.7126 | 0.6553 | 33.5104                       | 0.6320     | 2.83            |
| DCT [22]             | 35.4907                 | 16.9940                           | 4.2450                  | 1.6558 | 0.5752 | 37.9529                       | 0.7903     | 3.20            |
| RWT [23]             | 35.5209                 | 17.0745                           | 4.2121                  | 1.6571 | 0.5802 | 38.0320                       | 0.7934     | 4.80            |
| Fuzzy transform [24] | 32.5620                 | 6.0501                            | 1.4000                  | 1.7359 | 0.5784 | 32.6430                       | 0.4994     | 2.84            |
| NSST [30]            | 30.8917                 | 16.7671                           | 4.7653                  | 1.6847 | 0.6281 | 34.2038                       | 0.7868     | 2.92            |
| Proposed method      | 50.0227                 | 28.4437                           | 2.2885                  | 1.6868 | 0.5727 | 47.6598                       | 0.6043     | 3.47            |

The fifth pair consists of X-ray and VA images found in Figure 7 among other medical images. X-ray images demonstrate the density of various tissues. However, they don't say how thick the disease is. Conversely, VA appears to value the depth of the disease and is not influenced by the density of tissues.

Integrated with the two images, the diagnostic value of both modality images is greatly improved in comparison with the value of each individual image, and thus, both X-ray images and VA images possess more information. The study of breast cancer is further enhanced with the above fused image as illustrated in Figure 7(h), providing

more advanced study options of specific components of the breast. Table 5 includes an overall summary of the proposed method and the presence of other methods in the literature. When applying the proposed method, the maximum average gradient of a fused image is 16.3895 changes in intensity per pixel, with an entropy value of 7.3454 bits/pixel, and an estimated time of 2.81 seconds.

### 5.4 Subjective Evaluation

In many imaging applications, how humans perceive the output of combined images is crucial.

Subjective analysis was conducted through qualitative evaluations of fused images and was comprised of radiologists, doctors, researchers, academics, and students. The fused image was shown to 15 radiologists and 15 physicians who are proficient in assessing output image quality. The fused image was then presented to a subsample of researchers and students with a background in image processing and who are able to assess the output image's sharpness, and their average rating was recorded. Evaluations are rated on an absolute scale, an example of which is provided in Table 6. The assessment was completed by 50 people, and their ratings are provided in Table 7.

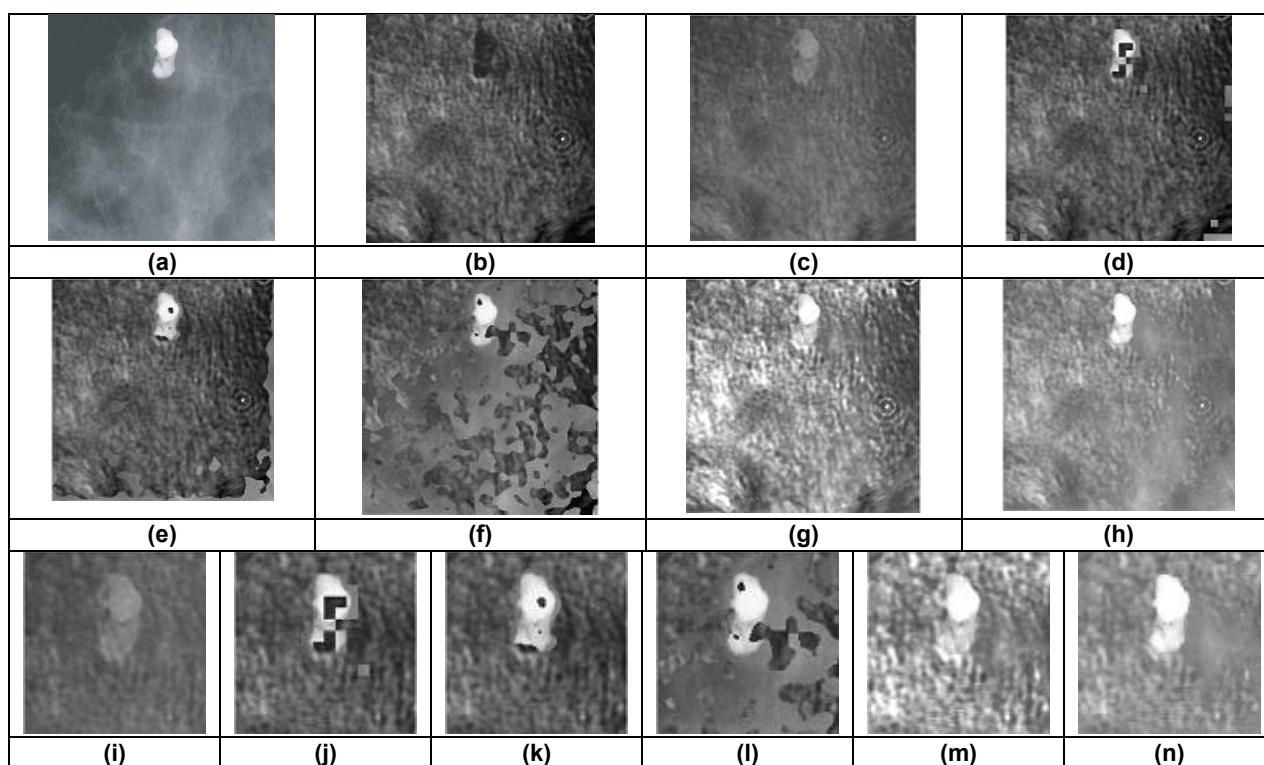


**Figure 7.** Results of Fusion for X-ray and VA images (a) X-ray image (b) VA image (c) Simple average (d) DCT (e) RWT (f) Fuzzy transform (g) NSST (h) The result achieved by the proposed method (i),(j),(k),(l),(m),(n) are magnified results of (c,d,e,f,g,h).

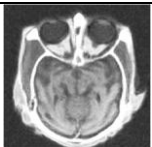
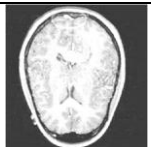
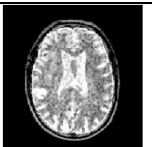
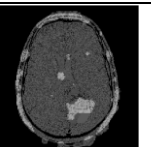
**Table 5.** Objective Evaluation of Spherical fuzzy set and other methods for figure 7.

| Fusion method        | SD (pixel intensity) | AG (change in intensity/pixel) | Entropy (bits/pixel) | FS     | CC     | SF (cycles/millimeter) | $Q^{AB/F}$ | CT (seconds) |
|----------------------|----------------------|--------------------------------|----------------------|--------|--------|------------------------|------------|--------------|
| Simple average [5]   | 20.4795              | 7.4844                         | 5.9657               | 1.9437 | 0.7590 | 16.1620                | 0.5129     | 2.10         |
| DCT [22]             | 32.5768              | 12.0194                        | 6.8302               | 1.6619 | 0.6712 | 20.2094                | 0.8010     | 3.37         |
| RWT [23]             | 31.3532              | 12.0816                        | 6.8101               | 1.6630 | 0.6510 | 20.2852                | 0.7376     | 6.81         |
| Fuzzy transform [24] | 34.3336              | 13.3243                        | 6.9364               | 1.9885 | 0.6360 | 23.9014                | 0.4738     | 2.92         |
| NSST [30]            | 25.9081              | 10.1473                        | 6.455                | 1.8863 | 0.6752 | 14.5812                | 0.6581     | 2.98         |
| Proposed method      | 42.7908              | 16.3895                        | 7.3454               | 1.7204 | 0.3758 | 20.2858                | 0.6736     | 2.81         |

**Table 6.** Scale for subjective quality assessment

| Scale | Evaluation | Depiction                                 |
|-------|------------|-------------------------------------------|
| 5     | Awesome    | A picture of the highest order.           |
| 4     | Decent     | A great photograph and it pleases the eye |
| 3     | Regular    | An acceptable photograph.                 |
| 2     | Not Good   | It was a blurry image, but it was there.  |
| 1     | Unusable   | An ugly image was unviewable.             |

**Table 7.** Standard rating scale for fused images from proposed method.

| Fused images of proposed method |  |  |  |  |  |
|---------------------------------|-----------------------------------------------------------------------------------|-----------------------------------------------------------------------------------|------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Observers who gave 5 rating     | 47                                                                                | 38                                                                                | 39                                                                                 | 46                                                                                  | 37                                                                                  |
| Observers who gave 4 rating     | 3                                                                                 | 7                                                                                 | 5                                                                                  | 4                                                                                   | 6                                                                                   |
| Observers who gave 3 rating     | 0                                                                                 | 3                                                                                 | 3                                                                                  | 0                                                                                   | 4                                                                                   |
| Observers who gave 2 rating     | 0                                                                                 | 2                                                                                 | 3                                                                                  | 0                                                                                   | 3                                                                                   |
| Observers who gave 1 rating     | 0                                                                                 | 0                                                                                 | 0                                                                                  | 0                                                                                   | 0                                                                                   |

## 6. Conclusion

This study presented a Bendlet-based framework for multimodal medical image fusion that combines curvature-aware multiscale decomposition with separate fusion rules for low- and high-frequency information. In the proposed procedure, the source images are decomposed into Bendlet coefficients representing low- and high-frequency subbands. Contrast Visibility is then applied to the low-frequency subbands to preserve intensity, contrast, and coarse anatomical information, while Modified Spatial Frequency is applied to the high-frequency subbands to retain edges, textures, and local structural variations. The fused image is subsequently reconstructed using the inverse Bendlet Transform. Evaluation across five medical-image databases, together with the visual comparisons and objective values reported in Tables 1–5, indicates that the proposed approach can preserve complementary information from the source modalities and improve the clarity of fused images relative to the comparison methods included in the manuscript. The method is particularly intended to represent curved and directional anatomical structures more effectively than conventional wavelet-based approaches. Nevertheless, the reported findings should be interpreted within the limits of the present study. The manuscript does not yet provide clinical-reader validation, statistical significance testing, runtime analysis, sensitivity analysis for the selected Bendlet parameters, or a component-wise ablation study of the CV and MSF rules. Future work

should therefore evaluate the method on larger and more diverse multimodal datasets, quantify robustness to registration errors and noise, compare computational complexity, and investigate whether learning-based or optimization-assisted fusion strategies provide consistent improvements. Clinical assessment by qualified readers would also be necessary to determine whether the observed image-quality gains translate into improved diagnostic interpretation.

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B. Muralidhar Naick: Conceptualization, Methodology, Writing - Original Draft. D. Leela Rani: Investigation, Writing - Review & Editing. V. Vijaya Kishore: Data curation, Visualization, Supervision. All authors read and approved the final version of the manuscript.

### Ethics Approval

This study used publicly available datasets and did not involve the collection of data from human participants or animals by the authors. Therefore, ethical approval was not required.

### Informed Consent

Informed consent was not required because this study used publicly available, anonymized datasets.

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The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

### Data Availability

The datasets analyzed during the current study are publicly available from the respective repositories cited in the manuscript.

### Has this article screened for similarity?

Yes

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