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Enhancing medical imaging: Leveraging discrete wavelet transform and its variants for advanced image fusion

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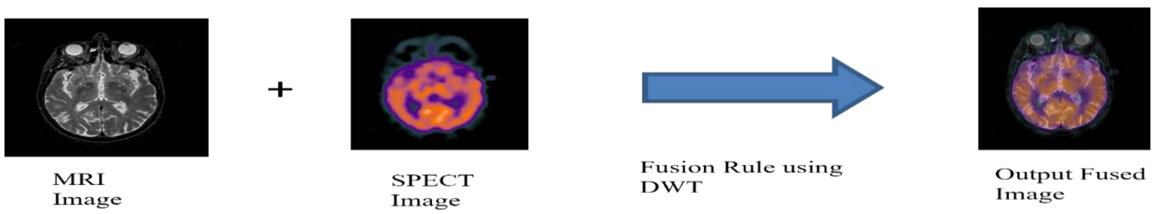
Article

ABSTRACT



Medical image fusion, or the technique of combining data from many medical images to create a single fused image, is crucial to modern therapeutic and diagnostic procedures. The Discrete Wavelet Transform (DWT) has emerged as a powerful tool for medical image fusion due to its ability to efficiently extract both global and local information from medical images. This paper provides an overview of recent advancements in DWT-based medical image fusion techniques. The paper reviews the fundamentals of DWT-based fusion and its variants, examines several fusion methods, and emphasizes applications in imaging modalities such as SPECT and MRI. This paper focuses on challenges and future directions for DWT-based medical image fusion. The suggested method improvises in performance measures by providing constants for the scale and orientation parameters.

Keywords: Discrete wavelet transforms (DWT), SPECT, PET-Positron emission tomography, Computed tomography, Image Fusion

INTRODUCTION

A vital method in contemporary medicine, medical image fusion combines data from several imaging modalities to give a more thorough picture of a patient's condition.[1] Comprehensive diagnosis, better treatment planning, better monitoring, and research and development are all aided by medical image fusion. Utilizing the advantages of many imaging modalities, medical image fusion offers a more thorough, precise, and detailed picture of the patient's condition. This technology improves patient outcomes, makes better use of healthcare resources, and advances medical research in addition to improving diagnostic and therapeutic capabilities.[2]

The DWT and its variant transform methods help express signals with multi-resolution characteristics. Its basis is the wavelet decomposition transform. Wavelets allow signals to be examined simultaneously in terms of both frequency and time; they condense energy into a single instant while retaining their wave-like structure. Since the Fourier transform cannot capture abrupt changes in the signal, DWT is utilized. When the signals are visual, this becomes even more useful since contrast and edges are unable to adequately capture the abrupt changes.[3]

The Fourier transform is a component of various sinusoids with varying frequencies, while wavelet constituents are various wavelets with various scales and placements. With the aid of these coefficients, the wavelet must meet the admissibility requirement and exhibit oscillatory behavior to recreate the original signal. Wavelet's time domain average must be zero for it to meet admissibility requirements. Furthermore, wavelets need to have an oscillating structure to exhibit wavelike behavior. The wavelet transform can be used to examine self-similarity in signals, trends, discontinuities in higher derivatives, and breakdown points when these two conditions are satisfied. As the proposed algorithm works on detail and approximated coefficients, the fusion rule consisting of scale and orientation information of images provides better visualization of the output image and also performs well in quantitative analysis over the DWT algorithm and its variants.

LITERATURE REVIEW

Multiscale decomposition (MSD) approaches are the most commonly used method in multimodal medical image fusion. Two

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classic MSD strategies are wavelet and pyramid-based methods. DWT allows for flawless localization in the time and spatial frequency domains while stably maintaining various frequency information. However, this approach does not satisfy the shift-invariance condition.Due to its reliance on decomposition levels and the fact that fusion speed is a component in the picture fusion process, the DWT algorithm suffers from computational complexity and time.[4] Thus, picture fusion can be completed more quickly with the aid of a GPU.[5] The source images are converted into the frequency transform domain. These domains are projected into local bases to convey sharpness. Transformed coefficients are utilized to identify salient features. These techniques yield spectral content of high quality. It has been demonstrated that wavelet-based image fusion is effective at capturing one-dimensional singularities. For isolated discontinuities, DWT performs well. This fusion approach is perfect as it only captures point-wise information in a limited number of directions. Shift variation DWT necessitates down sampling. The limited directionality of wavelet fusion is a limitation. Using a wavelet-based technique, more than one classifier scheme is needed to increase accuracy. Typically, adaptive selection , weighting of feature coefficients, and sub bands in frequency domains (e.g., DWT, DCT) are involved in dimensionality reduction. The selection of features must consider low correlation, high accuracy, and high discrimination. Compared to the original features, fewer features have been chosen. When comparing feature selection to subspace techniques like PCA, there are several benefits. Certain transformations, such as DCT and DWT, are quick and don't require training, and the precision of feature selection is on par with subspace.[6]Using multiscale transformations, source images are first divided into low- and high-frequency components. After that, various components are fused using the proper fusion criteria. Lastly, inverse transformation can be utilized to achieve the fused output.[7] Several algorithms for medical image fusion were looked up in this. Previous research has demonstrated that many methods were based on both the spatial and transform domains. That is, it allows spatial as well as various transformation processes. Hence in this DWT algorithm is implemented. The detailed algorithm is given below.

FUSION STRATEGIES

DWT has been used to generate several fusion strategies for the fusion of medical images, including.

1. Multiscale Fusion: Keeping both local details and global architecture intact by fusing data from several scales.
2. Modality fusion: Combining information from several imaging modalities to improve the precision of the diagnosis.
3. Feature-Based Fusion: To enhance lesion localization and identification, features derived from wavelet coefficients are selectively combined.
4. Region-of-Interest Fusion: To improve visualization and analysis, fusion is focused on particular regions of interest found in the input images.

An image and signal processing mathematical tool is the discrete wavelet transform or DWT. The process of fusing many images into one to improve visual perception or extract pertinent elements is known as image fusion. Because DWT can represent a picture in both the spatial and frequency domains, it is frequently used in image fusion.

- The basic steps of using DWT in image fusion are as follows.

1. Decomposition

Each input image at different scales or levels can be divided into high-frequency detail coefficients and low-frequency approximation coefficients using the DWT.. As a result, every image is represented in many resolutions.

2. Coefficient Fusion

From the decomposed images, choose the proper coefficients for fusing. Typically, high-frequency details are captured by the detail coefficients, while the approximation coefficients are employed to preserve the general structure and low-frequency information.

3. Fusion Rule

To merge the chosen coefficients, define a fusion rule. The fused coefficients are produced by combining the coefficients from various images according to this rule. Using a weighted average based on image quality or relevance, maximum selection, or simple averaging are common fusion rules.

4. Inverse DWT

Using the fused coefficients that were obtained in the previous step, apply the inverse DWT to recreate the fused image. The benefit of DWT for image fusion is that it can represent images at several resolutions, which makes the fusion process more adaptable and flexible. It enables the preservation of important features at different scales while efficiently representing both global and local details. There are other methods for fusing images, and the choice of fusion technique depends on the specific requirements and application. Moreover, more advanced techniques like the Stationary Wavelet Transform (SWT) or the Contourlet Transform may be researched for improved fusion performance in particular scenarios. Significant progress has been made in the Discrete Wavelet Transform (DWT) and its variant, broadening its applications in signal processing, data compression, image processing, and other domains while also enhancing performance.

NOTEWORTHY DEVELOPMENTS IN DWT INCLUDE ALGORITHMS AS FOLLOW

1. Fast Algorithms: Researchers have developed efficient algorithms for DWT computation, such as the Fast Wavelet Transform (FWT) and lifting schemes. These algorithms reduce computational complexity and memory requirements, making DWT practical for real-time applications and large-scale data processing.

2. Biorthogonal and Non-Separable Wavelets: These wavelets provide enhanced orthogonality, symmetry, and directional selectivity. They are the result of developments in wavelet design. These wavelets provide a better representation of complex signals and images, enhancing the performance of DWT-based techniques.

3. Wavelet Transforms That Are Shift-Invariant: Since conventional DWT is shift-variant, the wavelet coefficients can be greatly impacted by even minute changes in the input signal. This restriction is overcome by shift-invariant wavelet transforms, which offer a more reliable representation of signals and images under translation. The Undecimated Wavelet Transform (UWT)

and the Stationary Wavelet Transform (SWT) are two examples of these transformations.

4. Complex Wavelet Transforms: Complex wavelet transforms extend the real-valued DWT to the complex domain, enabling the analysis of both amplitude and phase information. Complex wavelet transforms offer improved directional selectivity and shift-invariance, making them suitable for applications such as texture analysis and image denoising.

5. Adaptive Wavelet Transforms: Adaptive wavelet transforms dynamically adjust the wavelet basis functions based on the local characteristics of the input signal or image. To better capture signal information, these transformations adaptively choose the wavelet sizes and orientations. This improves performance in applications like image fusion and feature extraction.

6. Sparse Representation and Compressive Sensing: Advances in sparse representation and compressive sensing have led to novel DWT-based techniques for signal and image reconstruction from limited or noisy measurements. Sparse representations exploit the sparsity of wavelet coefficients to reconstruct signals with high fidelity, even from highly under-sampled data.[8–11]

7. Fusion of Deep Learning and DWT: Current studies have investigated how to combine deep learning methods with DWT for tasks like image fusion, denoising, and super-resolution. Deep learning-based methods improve the performance of fusion algorithms by utilizing the hierarchical representations that DWT has learned, producing state-of-the-art outcomes in a range of applications.[12–15]

These advancements in DWT have significantly expanded its capabilities and applicability, enabling more efficient and accurate processing of signals and images in diverse fields ranging from medical imaging to remote sensing and beyond.

MATHEMATICAL EXPRESSION FOR DWT

In general, wavelet transforms are developed and used for both the general representation of image signals and its specific application to image compression. Furthermore, this study provides an outline of mathematical advances, followed by examples of picture coding from the perspectives of the transformations and spatial domains. Numerous non-stationary dynamical systems and frameworks generate time-frequency data, and the DWT has become a typical analytical tool for this type of data. Additionally, a multi-dimensional transform domain for separable image decompositions was examined, initially for image coding goals and subsequently for mathematical reasons. Image pixels can be transformed into wavelets via the Discrete Wavelet Transform method, which can then be applied to wavelet-based coding and compression.

The term "Discrete Wavelet Transform DWT" is defined as

$$W_{\phi(I0,K)} = \frac{1}{\sqrt{M}}(p) \sum_P f(p) \phi_{I0,k}(p) \ldots\ldots\ldots (1)$$

$$W_{\Psi_{(I,K)}} = \frac{1}{\sqrt{M}} \sum_P f(p) \Psi_{i,k}(p) \ldots\ldots\ldots (2)$$

For $i \geq i0$ the Inverse Discrete Wavelet Transform (IDWT) is defined as:

$$f(p) = \frac{1}{\sqrt{M}} \sum_x W_{\phi(I0,K)} \phi_{I0,k} p + \frac{1}{\sqrt{M}} \sum_{i-i0}^{\infty} \sum_k W_{\Psi_{(I,K)}} \Psi_{i,k}(p) \ldots\ldots\ldots (3)$$

Where $f(p)$, $\phi_{i0,k}(p)$, $\Psi_{i,k}(p)$ are the discrete variable's functions. The $\tilde{\phi}_{I0,k}(p)$ is one of the expansion functions that are obtained via translating and scaling using a scaling function (p). functions of the discrete variable. The $\phi_{I0,k}(p)$ is a member of the set of expansion functions derived from a scaling function (p), by translation and scaling using.

$$\phi_{I,k} p = 2^i \phi(2^i p - k) \ldots\ldots\ldots (4)$$

The $\phi_{I,k} p$ is a wavelet that is part of the wavelet set that is obtained by translating and scaling a wavelet function (p) utilizing the

$$\Psi_{i,k} p = 2^{i/2} \Psi(2^i p - k) \ldots\ldots\ldots (5)$$

The translated and scaled basis elements for the 2D wavelet transform are given by,

Table 1. Scaled and Translated basis elements of the Image.

Frequency band	**Scaled and translated basis elements**	**Detailed Scaled and translated basis elements**
$LL_{1\&2}$	ϕ p, q	ϕ(p) ϕ(q)
$LH_{1\&2}$	ψ H p, q	ψ(p) ϕ(q)
$HL_{1\&2}$	ψ V p, q	ϕ (p) ψ (q)
$HH_{1\&2}$	ψ D p, q	ψ(p) ψ(q)

where the decomposition direction of the wavelet is indicated by the superscripts H for horizontal, V for vertical, and D for diagonal. Wavelets in two dimensions are used in image alteration. A multiresolution representation of the 2-D wavelet and scaling functions is shown below.

$$\phi_{i,m,n}(p,q) = 2^{i/2} \phi(2^i p - m, 2^i q - n) \ldots\ldots\ldots (6)$$

$$\Psi_{i,m,n}(p,q) = 2^{i/2} \Psi(2^i p - m, 2^i q - n) \ldots\ldots\ldots (7)$$

Where J={*H-Horizontal*,*V-Vertical*,*D-Diagonal*}

Table 2. The following is the discrete wavelet transforms function f(p, q) of size *M x N*

Scaling function of the wavelet representation	$\mathbf{W_{\phi(io,m,n)}} = \frac{1}{\sqrt{MN}} \sum_{P=0}^{M-1} \sum_{Q=0}^{N-1} \boldsymbol{f(p,q)}\, \phi_{i0,m,n}(\boldsymbol{p,q})$ …………(8)
Horizontal subband representation	$W_{\Psi}^{H}(i,m,n) = \frac{1}{\sqrt{MN}} \sum_{P=0}^{M-1} \sum_{Q=0}^{N-1} f(p,q)\, \Psi_{i,m,n}^{H}(p,q)$…………(9)
vertical subband representation	$W_{\Psi}^{V}(i,m,n) = \frac{1}{\sqrt{MN}} \sum_{P=0}^{M-1} \sum_{Q=0}^{N-1} f(p,q)\, \Psi_{i,m,n}^{V}(p,q)$………(10)
Diagonal subband representation	$W_{\Psi}^{D}(i,m,n) = \frac{1}{\sqrt{MN}} \sum_{P=0}^{M-1} \sum_{Q=0}^{N-1} f(p,q)\, \Psi_{i,m,n}^{D}(p,q)$……………………(11)

The inverse discrete wavelet transform for the image signal can be simply obtained from the scaling and wavelet functions, $W\phi$ and Ψ, previously discussed.

$$f(p,q) = \frac{1}{\sqrt{MN}} \sum_m \sum_n W_{\phi}(i0,m,n) \phi_{i0,m,n}(p,q) + \frac{1}{\sqrt{MN}} \sum_{j=H,V,D} \sum_{i=i0}^{\infty} \sum_m \sum_n W_{\Psi}^{j}(i,m,n) \Psi_{i,m,n}^{j}(p,q) \ldots\ldots\ldots (12)$$

A 3-D wavelet divides a set of three-dimensional images into several slices according to the X, Y, and Z directions. There are different frequency bands in each slice.

$$LLL = \phi\, p, q, r = (\,p)\ \phi(\,q)\ \phi(r)$$
$$LLH = \psi 1\ p, q, r = \phi\,(p)\ \phi\,(q)\ (\,r)$$
$$LHL = \psi 2\ p, q, r = \phi\,(p)\ (q)\ (r\,)$$
$$LHH = \psi 3\ p, q, r = \phi\,(p)\ (q\,)\ \psi\,(r)$$
$$HLL = \psi 4\ p, q, r = \psi\,(p)\ \phi\,(q)\ (\,r)$$
$$HLH = \psi 5\ p, q, r = \psi\,(p)\ (q\,)\ (\,r)$$
$$HHL = \psi 6\ p, q, r = \psi\,(p)\ (\,q)\ (\,r)$$
$$HHH = \psi 7\ p, q, r = \psi\,(p)\ (q\,)\ \psi\,(r)$$

In the DWT transform, wavelets are sampled at discrete intervals. It provides information about the image in both the frequency and spatial domains. A combination of decimation and filter bank analysis can be used to analyze an image. It offers signal analysis in terms of both frequency and duration. Even when energy is concentrated in space, its periodic wave structure remains intact. A flexible mathematical tool for transient analysis is DWT. Analyzing non-stationary or mathematically unpredictable data is tremendously beneficial. When it comes to image processing, the borders of the image are typically where abnormalities and distinctiveness can be found.

To give the lower frequency sub bands more frequency resolution and coarser temporal precision than the higher frequency sub bands, DWT splits a digital signal into discrete sub bands.

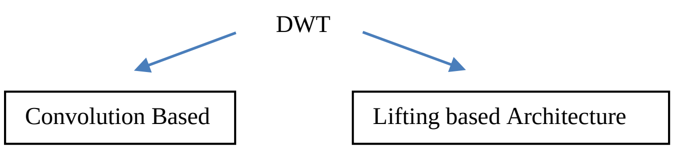


Figure1. TWO approaches DWT.

Convolution-based: This approach is suited for software implementation of Image processing applications.

Lifting-based Architecture: This approach is well suited for hardware implementation where on-chip memory is less.

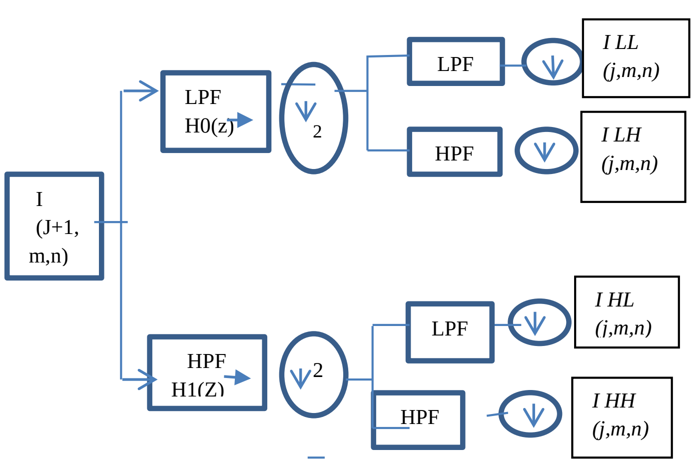


Figure 2. Single-level 2D-DWT basic decomposition structure

In Figure 2. The representation of I is I [(j+1), m,n] where I is the original image, m-represents rows, n-represents columns, and j+1 is the scale. The transfer functions for this image are H0(z) and H1(z), respectively, for the low-pass and high-pass filters.

The application causes the signal to divide into two frequency bands, which in turn causes the signal's bandwidth to decrease by half. Redundant samples are obtained when a signal separates into a high-frequency band and a low-pass band. Using the Nyquist criteria, half of the sample counts are deleted from a signal without losing any information. Therefore, a downsample operation of 2 is applied at both the LPF and HPF outputs to achieve this. This signal was again applied to the signal's rows after being filtered and down-sampled. The subbands *ILL(j,m,n), ILH(j,m,n), IHL(j,m,n), and IHH (j,m,n)* resp. are acquired at the output of these filters.

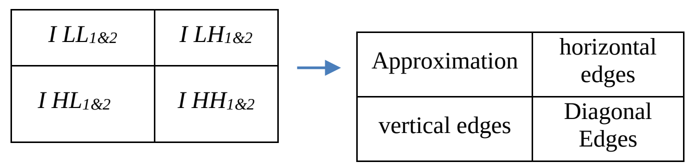


Figure 3. Level 1- Decomposition

Since *ILL(j,m,n)* has gone through two low-pass filters, an approximation of the input image is provided. After going through LPF and HPF, which are applied to the image's rows, ILH(j,m,n) extracts the image's horizontal features. IHL(j,m,n) will extract the vertical features applied to the image's columns.IHH(j,m,n) highlights the edges of the image which is taken over as an input along its diagonals. In Fig. no. 3, this is displayed.

Proposed System Block Diagram

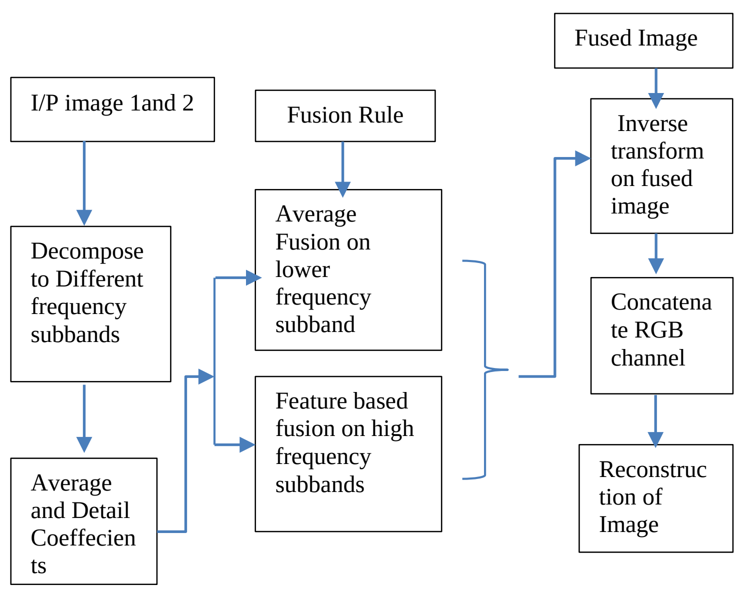


Figure 4. Proposed system block diagram for Medical Image fusion.

In this proposed system block diagram two input images, mainly MRI and SPECT images are used. To separate the two images into their respective frequency sub bands, a succession of low-pass and high pass filters were applied. These frequency sub bands contain the detail and approximated coefficients, which contain information of images. These wavelet coefficients can be interpreted in terms of their magnitude and phase, the magnitude provides information about the amplitude of features at different scales and orientations, while the phase provides information about the location and structure of these features. This fused image will be recovered from Inverse DWT and inverse fusion rule. Fused images will be assessed according to the different performance parameters as shown in the below table. To evaluate the fused image output, this study includes the mutual information (MI), peak signal-to-noise ratio (PSNR), and structural similarity index (SSIM) metrics. Mutual information measures the amount of information that fused image shares with source images. The structural similarity index (SSIM) assesses the similarity between the fused image and the source images in terms of structure, luminance, and contrast. An improved output image quality is indicated by a greater peak signal-to-noise ratio.

Table 3. Performance parameters to asses output fused image

Sr. No.	Performance Parameter	Mathematical Formula	Significance
1.	Structural Similarity Index (SSIM)	$SSIM(x,y) = (\frac{(2\mu_x\mu_y + C1)(2\sigma_{x,y} + C2)}{\left((\mu_x^2) + (\mu_y^2) + C1\right)(\sigma_x^2 + \sigma_y^2 + C2)}$	(-1,1) This performance measure indicate similarity between ground truth image and output image.
2.	Peak Signal to Noise Ratio(PSNR)	$PSNR = 20\, log_{10}(\frac{MAX}{\sqrt{MSE}})$	This ratio must be high ,which represents good quality of image and viceversa.
3.	Mutual Information (MI)	$I(A,B) = \sum_{b\in B}\sum_{a\in A} p(a,b) * \log\frac{p(a,b)}{p(a,b)}$	This performance measure indicates mutual information content in both the images.(i.e. ground truth image and fused output image).

Implementation Steps

1.Give input images (MRI,SPECT)

2.Convert Images into RGB channels.

3.Apply decomposition technique to both input images.

4.Extract LL,LH,HL,HH coefficients

5.Apply average fusion to LL subband output

6.Pad output images with zeros .

7.Check each RGB channel for both images and apply fusion rule.

8.Perform Inverse Discrete Fourier Transform on RGB channel

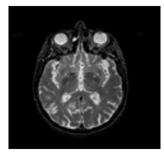
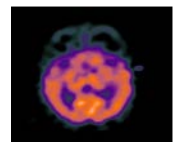
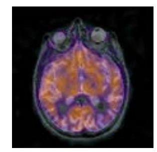
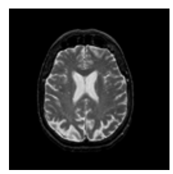
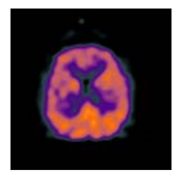
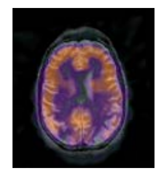
9.Concate RGB channel.

10.Display output.

Experimental Result And Discussion

The current approach is used on brain MRI and SPECT pictures. A core i5 processor and MATLAB 2016(a) are utilized for the experimental work. There is an increase in the amount of information obtained, a diversity of MRI imaging techniques, and a complexity of imaging concepts. However, SPECT pictures are produced by radionuclides that emit single photons. The information received is more abundant, MRI imaging techniques are becoming more varied, and imaging concepts are becoming more complex. On the other hand, radionuclides that release single photons are used to create SPECT pictures.

Table 4. Input images and their ground truth images

	MRI Image /Input Image 1	SPECT Image /Input Image2	Ground Truth Fused Image
SET 1 IMAGE INPUT			
SET 2 IMAGE INPUT			

SPECT images reveal an organ's functional behavior. DWT algorithm comes under transform domain, as in this algorithm single level 2-dimensional structure is applied which gives the Pixel level image fusion. Above table no.4 shows the set of MRI and SPECT input images and their ground truth fused images in third column. These ground truth images are used to asses the output fused images of existing and proposed algorithm.

Table 5. Output Fused Images for different transform algorithms

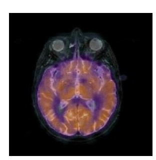
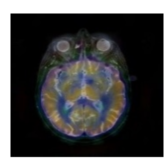
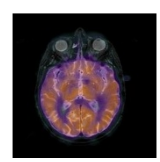
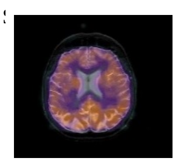
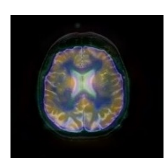
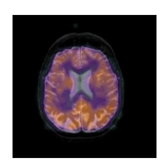
	DWT	Dual tree complex wavelet transform	Multiwavelet Transform
SET 1 FUSED IMAGE OUTPUT			
SET 2 FUSED IMAGE OUTPUT			

Table 6. Performance measures for two sets of images

Image Set	*Techniques Applied*	*SSIM*	*MI*	*PSNR*
SET 1	Single Level Discrete wavelet decomposition	0.401	1.45	18.234
	Dual tree complex wavelet transforms	0.423	1.56	20.121
	Multiwavelet transform	0.511	1.61	20.546
	Proposed Method	0.783	2.45	21.345
SET 2	Single Level Discrete wavelet decomposition	0.412	1.47	18.235
	Dual tree complex wavelet transforms	0.426	1.66	20.143
	Multiwavelet transform	0.513	1.76	20.756
	Proposed Method	0.789	2.68	22.345

Table no.5 shows the output fused images for the algorithm mainly DWT, Dual tree complex wavelet transform and Multiwavelet transform for two sets of input images. Figure no.5 and 6 shows the output of proposed algorithm. Their results for performance measures are enlisted in table no.6

Figure 6. Set 1 Proposed method output

Figure 7. Set 2 Proposed method output

In this MRI and SPECT images are first converted into RGB channels, after this conversion the DWT decomposition technique is applied over these RGB channels which are of size 128 by 128 each and the fusion rule is applied. Following the application of the decomposition procedure, the inverse discrete wavelet transforms, and the fused image is recovered by applying the inverse fusion rule.

The low pass filter in this experiment creates approximations by splitting the input images into lower and higher frequency bands, and the high pass filter eliminates the edges. Using the inverse discrete wavelet transform and inverse fusion rule, the fused image is obtained following the use of the decomposition process.

From the table no.6, it is observed that the proposed algorithm performs well over existing algorithms stated in this paper. Since all the approaches presented are not entirely shift-invariant and can alter wavelet coefficients dramatically with even a slight shift in the input signal, the proposed method yields improved performance metrics. Moreover, its wavelet basis lacks directionality and orientation, which can prevent it from capturing the characteristics of multidimensional signals. When acquiring or processing signals, it could result in noise distortion. Due to the employment of a parallelogram with the help of a discrete localizing window – where two constants exist for each scale and orientation.

The suggested solution overcomes these drawbacks. The proposed algorithm used the base of frequency band decomposition and at the same time, the scale and orientation information are also preserved which helps to give a better result of the proposed algorithm.

Conclusion And Future Scope

Spectrum and color distortion are the outcomes of the spatial domain approach, notwithstanding its simplicity of usage and low processing complexity. The Transform Domain only offers spectrum information in the absence of directional information, which can have significant blocking effects and result in a significant loss of source information. Information loss occurs from shift variation in DWT and its variant. By preserving scale and orientation information output image gives better results for performance parameters. However, the suggested technique outperforms another algorithm by using directional information obtained from scale and orientation added to the fusion rule. The studies described in the following publications were conducted utilizing a variety of public and private datasets due to the vastness of the medical profession. The processing complexity is a major concern as medical images have bountiful information. According to a recent study, the Deep Learning technique is appropriate for application in medical image fusion approaches due to its capacity to parallel programs, enhance visual quality, and provide a range of quantitative evaluation alternatives. A recent study discovered that the hybrid domain, also known as the domain of the transformation, can help produce better-fused picture outputs for accurate medical diagnosis and therapy in addition to the deep learning technique.

Conflict of Interest

Authors declare that there is no conflict of interest academic or financial for publication ofthis work.

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