# Multimodal Medical Image Fusion Using Various Hybrid Fusion Techniques For clinical Treatment Analysis

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***Abstract:***Medical image fusion is one the most significant and useful disease analytic techniques. This research paper proposed and examines some of the hybrid multimodality medical image fusion methods and discusses the most essential advantages and disadvantages of these methods to develop hybrid multimodal image fusion algorithms that improve the feature of merged multimodality therapeutic image. Computed Tomography, Magnetic Resonance Imaging, Positron Emission Tomography and Single Photon Emission Computed Tomography are the input multimodal therapeutic images used for fusion process. An experimental results of proposed all hybrid fusion techniques provides the best fused multimodal medical images of highest quality, highest details, shortest processing time, and best visualization. Both traditional and hybrid multimodal medical image fusion algorithms are evaluated using several quality metrics. Compared with other existing techniques the proposed technique experimental results demonstrate the better processing performance and results in both subjective and objective evaluation criteria. This is favorable, especially for helping in accurate clinical disease analysis.

***Keywords:***Multimodal medical image fusion, MRI, PET, SPECT, PCA, DCT, DWT, DCHWT, GIF, curvelet transform, Sub-band Decomposition, Ridgelet Transform, PCNN, Neuro-Fuzzy

# 1 Introduction

The frequent development of medical imaging and information processing technologies provides many types of multimodality therapeutic images for clinical disease analysis. The medical images are broadly used in disease analysis, treatment centre, and radiation treatment. However, the obtained sensor responses of different modalities of medical images express different information about the human body, organs, and cells, and have their personal utilize. Image fusion is the mixture of two or more different images to form a novel image by using certain techniques. It is extracting information from multi-source images and improves the spatial resolution for the original multi-spectral image and preserves the spectral information. Image fusion can be classified into three levels Pixel level fusion, Feature level fusion and Decision level fusion. Pixel-level fusion having a large portion of the remarkable data is protected in the merged image. Feature-level fusion performs on feature-by-feature origin, such as edges, textures. Decision-level fusion refers to make a final merged conclusion. The image fusion decrease quantity of information and hold vital data. It make new output image that is more appropriate for the reasons for human/machine recognition or for further processing tasks. Image fusion is classified into two types' single sensor and multi sensor picture combination consolidating the pictures from a few sensors to shape a composite picture and their individual pictures are converged to acquire an intertwined image Ex: Multi focus and Multi Exposure fusion. Multi sensor image fusions merge the images from several sensors to form a composite image and their individual images are merged to obtain a fused image. Ex: medical imaging, military area. Multimodality medical images categorized into several types which include computed tomography (CT),magnetic resonance angiography (MRA), magnetic resonance imaging (MRI), positron emission tomography (PET), ultra sonography (USG), nuclear magnetic resonance(NMR) spectroscopy, single photon emission


doi: 10.18686/scr.v2i4.594

computed tomography (SPECT), X-rays, visible, infrared and ultraviolet. MRI, CT, USG and MRA images are the structural therapeutic images which afford lofty resolution images. PET, SPECT and functional MRI (fMRI) images are functional therapeutic images which afford low-spatial resolution images with functional information. Anatomical and functional therapeutic images can be incorporated to obtain more constructive information about the same object. Medicinal image fusion reduces storage cost by storing the single fused image instead of multiple-input images. Multimodal medical image fusion uses the pixel level fusion. Different imaging modalities can only provide limited information. Computed Tomography image can display accurate bone structures. Magnetic Resonance Imaging image can expose regular and pathological soft tissues. The fusion of CT and MRI images can integrate complementary information to minimize redundancy and improve diagnostic accuracy. Combined PET/MRI imaging can extract both functional information and structural information for clinical diagnosis and treatment. Positron emission tomography images can provide functional eloquent brain regions such as motor or speech regions by using specific activation tasks. In addition, single-photon emission computed tomography images reveal clinically significant metabolic change. Therefore, single multimodal image often cannot provide enough information to doctors in actual clinical situations. It is usually necessary to combine the multimodal images of different modalities to obtain more comprehensive information on diseased tissue or organs. Effective combining methods to use image fusion technologies, which can be automatically, combine multimodal medical images. The fused multimodal medical image not only obtains a more accurate and complete description of a target, but also reduces randomness and redundancies produced by the sensor in the medical image. Multimodal medical Image fusion increases the effectiveness of image-guided disease analysis, diagnoses and the assessment of medical problems. Image fusion having several applications like medical imaging, biometrics, automatic change detection, machine vision, navigation aid, military applications, remote sensing, digital imaging, aerial and satellite imaging, robot vision, multi focus imaging, microscopic imaging, digital photography and concealed weapon detection. Multimodal medical imaging plays a vital role in a large number of healthcare applications including medical diagnosis and treatment. Medical image fusion combining multiple images into form a single fused modalities. Medical image fusion methods involve the fields of image processing, computer vision, pattern recognition, machine learning and artificial intelligence.

The research paper is organized as follows. Sec. 2 describes the literature survey on related works. Sec. 3 discusses the proposed research work method both traditional and hybrid multimodal medical image fusion techniques. Sec. 4 performance evaluation metrics is briefly reviewed. Sec. 5 describes the implemented multimodal medical image fusion experimental results and performance comparative analysis. Finally, Sec. 6 concludes the paper.

## 2 Related Works

B.Rajalingam, Dr. R.Priya [1] proposed an efficient multimodal therapeutic image fusion approach based on both traditional and hybrid fusion techniques are evaluated using several quality metrics. B.Rajalingam, Dr. R.Priya [2] Proposed a novel multimodal medicinal image fusion approach based on hybrid fusion techniques. Magnetic resonance imaging, positron emission tomography and single photon emission computed tomography are the input multimodal therapeutic brain images and the curvelet transform with neural network techniques are applied to fuse the multimodal medical image. B.Rajalingam, Dr. R.Priya [3] proposed a novel neuro-fuzzy hybrid multimodal medical image fusion technique to improve the quality of fused multimodality medical image. Srinivasa Rao D, Seetha, *et al* [4] proposed image fusion using fuzzy and neuro fuzzy logic approaches operate to merge the images from different sensors, in order to improve visualization. Saad M. Darwish [5] proposes an image fusion system for medical engineering based on contourlet transform and multi-level fuzzy reasoning technique in which useful information from two spatially registered medical images is integrated into a new image that can be used to make clinical diagnosis and treatment more accurate. Sudeb Das, Malay Kumar Kundu [6] introduce a novel approach to the multimodal medical image fusion problem, employing multi scale geometric analysis of the nonsubsampled contourlet transform and fuzzy-adaptive reduced pulse-coupled neural network. C. T. Kavitha, C.Chellamuthu [7] proposes image fusion based on Integer

Wavelet Transform (IWT) and Neuro- Fuzzy. The anatomical and functional images are decomposed using Integer Wavelet Transform. The wavelet coefficients are then fused using neuro-fuzzy algorithm. Meenu Manchanda, Rajiv Sharma [8] proposed a novel method of multimodal medical image fusion using fuzzy-transform. FTR based fusion helps in preservation as well as effective transfer of detailed information present in input images into a fused image. Yong Yang, Yue Que, *et al* [9] proposed a novel multimodal medical image fusion method that adopts a multi scale geometric analysis of the non sub sampled contourlet transform with type-2 fuzzy logic techniques. Jiao Du, Weisheng Li, Ke Lu.[10] proposed the multimodal medicinal image fusion for the image disintegration, image restoration, image mixture rules and image excellence assessments. Therapeutic image fusion has been broadly used in medical assessments for disease diagnose. Xiaojun Xua, Youren Wang, *et al*. [11] proposed a multimodality medicinal image mixture algorithm based on discrete fractional wavelet transform. The input therapeutic images are decomposed using discrete fractional wavelet transform. The sparsity character of the mode coefficients in subband images changes. Xingbin Liu, Wenbo Mei, *et al*. [12] proposed a new technique namely Structure tensor and non subsampled shearlet transform to extract geometric features. A novel unified optimization model is proposed for fusing computed Tomography (CT) and Magnetic Resonance Imaging images. K.N. Narasimha Murthy and J. Kusuma [13] proposed Shearlet Transform to fuse two different images Positron Emission Tomography and Magnetic Resonance Imaging image by using the Singular Value Decomposition to improve the information content of the images. Satishkumar S. Chavan, Abhishek Mahajan, *et al*. [14] introduced the technique called Nonsubsampled Rotated Complex Wavelet Transform combining CT and MRI images of the same patient. It is used for the diagnostic purpose and post treatment review of neurocysticercosis. S. Chavan, A. Pawar, *et al*. [15] innovated a feature based fusion technique Rotated Wavelet Transform and it is used for extraction of edge-related features from both the source modalities. Heba M. El-Hoseny, El-Sayed M.El.Rabaie, *et al*.[16] proposed a hybrid technique that enhance the fused image quality using both traditional and hybrid fusion algorithms(Additive Wavelet Transform and Dual Tree complex wavelet transform. Udhaya Suriya TS, Rangarajan P [17] implemented an innovative image fusion system for the detection of brain tumors by fusing MRI and PET images using Discrete Wavelet Transform. Jingming Yang, YanyanWu,*et al*.[18] described an Image fusion technique Non-Subsampled Contourlet Transform to decompose the images into low pass and high pass subbands. C.Karthikeyan, B. Ramadoss [19] proposed the fusion of medical images using dual tree complex wavelet transform and self-organizing feature map for better disease diagnosis. Xinzheng Xu,Dong Shana,*et al*.[20] introduced an adaptive pulse-coupled neural networks, which was optimized by the quantum-behaved particle swarm optimization algorithm to improve the efficiency and quality of QPSO. Three performance evaluation metrics is used. Jyoti Agarwal and Sarabjeet Singh Bedi, *et al* [21] innovate the hybrid technique using curvelet and wavelet transform for the medical diagnosis by combining the Computed Tomography image and Magnetic Resonance Imaging image. Jing-jing Zonga and Tian-shuang Qiua [22] proposed a new fusion scheme for medical images based on sparse representation of classified image patches In this method, first, the registered input images are separated into confidential patches according to the patch geometrical route, from which the corresponding sub-dictionary is trained via the online dictionary learning algorithm and the least angle regression algorithm to sparsely code each patch; second, the sparse coefficients are combined with the choose-max fusion rule Finally, the fused image is reconstructed from the combined sparse coefficients and the corresponding sub-dictionary. Richa Gautam and Shilpa Datar [23] Proposed a method for fusing CT (Computed Tomography) and MRI (Medical Resonance Imaging) images based on second generation curvelet transform. Proposed method is compared with the results obtained after applying the other methods based on Discrete Wavelet Transform, Principal Component Analysis and Discrete Cosine Transform. Jiao Du, Weisheng Li, Bin Xiao, et.al [24] proposed an approach union Laplacian pyramid with multiple features for accurately transferring salient features from the input medical images into a single fused image. Zhaobin Wang, Shuai Wang, Ying Zhu, *et al*. [25] described the statistical analysis PCNN and some modified models are introduced and reviewed the PCNN's applications in the field of image fusion. Zhaobin Wang, Shuai Wang, *et al*. [26] proposed a novel guided filtering based weighted average technique to make full use of spatial consistency for fusion of the base and detail layers. B. K. Shreyamsha Kumar [27] proposed a discrete cosine harmonic wavelet transform based image fusion to retain the visual quality and performance of the merged image with reduced computations.

## 3 Proposed Research Work

### 3.1 Traditional Multimodal Medical Image Fusion Techniques

This paper implements different traditional image fusion algorithms for different types of multimodality medical images as shown in Figure. 1

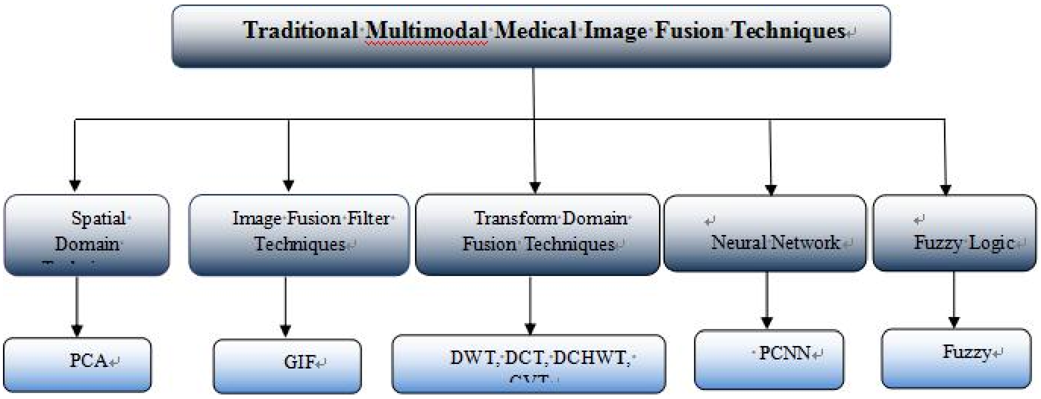



**Figure 1**: Traditional multimodal medical image fusion techniques

### 3.1.1 Principal Component Analysis (PCA)

Principal component analysis is one of the well-known techniques used for measurement decrease, feature removal and data revelation. In general, PCA is defined by the conversion of an elevated dimensional vector space into a near to the ground dimensional vector space. This property of PCA is helpful in reducing the amount of the therapeutic image data which is of large size without losing essential information. In this method a number of simultaneous variables are altered into uncorrelated variables called principal components. Each principal component is taken in the route of highest variance and lie in the subspace at right angles to one another.

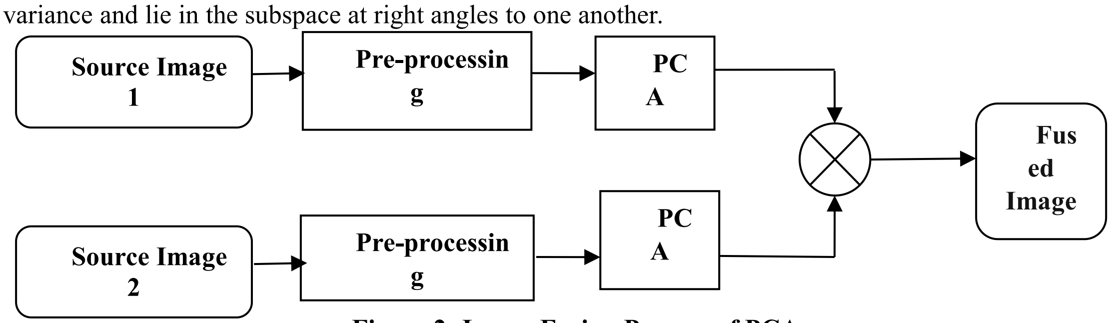



**Figure 2: Image Fusion Process of PCA**

#### 3.1.1.1 Procedural steps for image fusion using PCA algorithm

1) Convert the two input multimodal images into column vectors and make a matrix ‘B’ using these two column vectors.

2) Calculate the empirical mean vector along each column and subtract it from each of the columns of the matrix.

3) Calculate the covariance matrix ‘R’ of the resulting matrix.

4) Calculate the eigen values K and eigen vectors E of the covariance matrix.

5) Select the eigenvector equivalent to well-built eigen value and divide its each element by mean of that eigenvector. This will give us first principal component P1. Repeat the same procedure with eigenvector corresponding to smaller eigen value to get second principal component P2.

$$P_1 = \frac{R(1)}{\sum R} P_2 = \frac{R(2)}{\sum R}$$

6) Final Fused multimodal medical image is obtained by

$$I_f(x,y) = P_1 I_1(x,y) + P_2 I_2(x,y) \qquad (1)$$

### 3.1.2 Image Fusion with Guided Filtering

Currently, in medical image processing energetic research topic is edge preserving filter technique. Image processing has several edge preserving smoothing filtering techniques such as guided filter, weighted least squares and bilateral filter. Among the several filter techniques the guided image filter is giving better results and less execution time for fusion process. This image fusion filter method is based on a local linear form, creating it eligible for other image processing methods such as image matting, up-sampling and colorization. A multi-level representation is utilized by average smoothing filter. Subsequently, based on weighted average fusion technique, the guided image filter fuses the bottom and feature layers of multi-modal medical images.

### 3.1.2.1 Multi-level Image Decomposition

The average filter used to decompose the input multimodal medical images into multilevel representations. The bottom layer of each input image is represented by.

$$E_n = S_n * K \qquad (2)$$

Where the $n^{th}$ input image is denoted as $S_n$, average filter is represented by K and the 31×31 conventional matrix is set to average filter size. First the bottom layer is found then the feature layer can be simply computed by subtracting the bottom layer from the input medical images.

$$F_n = S_n - E_n \qquad (3)$$

The aim of the multi-level decomposition step is to separate each input medical images into bottom and feature layer. A bottom layer contains the huge level variations in strength and a feature layer contains the minute level information.

### 3.1.2.2 Guided image filter with weight map construction

The Gaussian filtering is applied on both the input multimodality medical images to get the high pass multimodal medical image $R_n$.

$$R_n = S_n * M \qquad (4)$$

Where the Gaussian filters is represented by M with 3 × 3 matrix. Construct the saliency maps $P_n$ using the local average value of $R_n$.

$$P_n = |R_n| * v_{r_v \sigma_v} \qquad (5)$$

Where Gaussian low pass filter is denoted by v and $(2r_v + 1)$ $(2r_v + 1)$ is the size of low pass filter and the $r_v$ and $\sigma_v$ parameters of the Gaussian filters. The calculated saliency weight maps are giving good description and detail information of the saliency intensity. After that, the saliency weight maps are compared to establish the weight maps are represented by,

$$T_x^k = \begin{cases} 1 \text{ if} P_1^\kappa = \max (P_1^\kappa, P_2^\kappa \ldots\ldots, P_X^\kappa) \end{cases} \qquad (6)$$

Where the number of input multimodal medical images is represented by X, the saliency value of the pixel k in the $n^{th}$ image is $P_x^k$. But, the artifacts of the merged image which may produce the weight maps with noisy and not associated with object limitations. The effective way to solve the above problem is to use spatial consistency. Spatial consistency is two adjacent pixels have identical clarity or color, they will be apt to have comparable weights. The formulating an energy function is based on spatial consistency fusion approach. To get the essential weight maps this energy function can be minimized globally. But, the optimization based methods are often somewhat incompetent. Guided image filtering is performed on every weight map $T_n$ with the equivalent input image $S_n$ serving as the supervision image.

$$W_n^E = V_{r_1 \varepsilon_1}(T_n, S_n) \qquad (7)$$

$$W_n^F = V_{r_1 \varepsilon_1}(T_n, S_n) \qquad (8)$$

Where the guided image filtering parameters are represented by $r_1, \varepsilon_1, r_2,$ and$\varepsilon_2$, the weight maps of the bottom and features layers denoted by $W_n^E$ and$W_n^F$. N is normalized weight maps value and each pixel k is sum to one. The inspiration of the weight maps construction technique is represented in the following expression. The eqn.1, eqn. 3 and eqn. 4 derived the local variance point i is referred by its value very small and the supervision image having pixel in very large, then $a_k$ will become close to 0 and the filtering output R will equal to $\overline{T_k}$. If the local variance of pixel i having very large value, then the i is represent the pixel edge area, next $a_k$ will become far from zero. As established in,

$\nabla R \approx \bar{a}\nabla S$ will turn into accurate, which means that only the weight map in one side of the edge will be averaged. In both situations, those pixels with identical color or clarity tend to have comparable weights. In contrast, sharp and edge-aligned weights are preferred for merging the feature layers because details may be lost when the weights are over-smoothed. Hence, a large filter size and a large blur degree are chosen for merging the bottom layers, while a minute filter size and a minute blur degree are chosen for the feature layers.

#### 3.1.2.3 Multi-level Image re-enactment

Multi-level image reconstruction contains the following two steps. Initially, the bottom and feature layers of different input multimodal medical images are combined together using weighted averaging filtering

$$\bar{E} = \sum_{n=1}^{N} W_n^E E_n \qquad (9)$$

$$\bar{F} = \sum_{n=1}^{N} W_n^F F_n \qquad (10)$$

Next, the merged output multimodal medical image R is obtained by combining the merged bottom layer $\bar{E}$ and the merged feature layer $\bar{F}$

$$R = \bar{E} + \bar{F} \qquad (11)$$

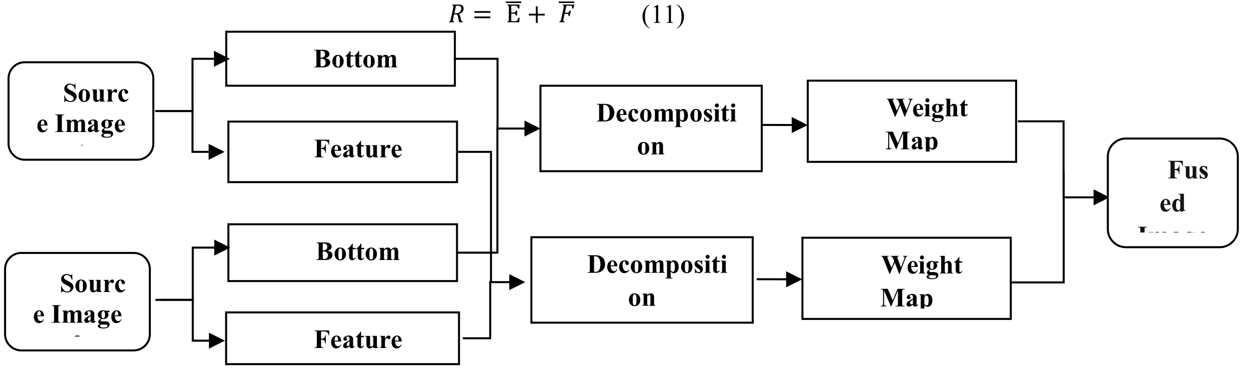



**Figure 3: Image Fusion Process of Guided Filtering**

#### 3.1.2.4 Procedural steps for image fusion using Guided Image Filtering

1) Take the two input multimodal medical images.

2) Resize both images into 512 x 512 dimensions.

3) Decompose the input multimodal medical images using average filtering.

4) Separate the input multimodality medical images into bottom layer and feature layer based on multi scale representation.

5) Apply the Gaussian laplacian filters for to construct the weight map and saliency map.

6) Perform the image reconstruction and get the final fused multimodal medical image.

### 3.1.3 Discrete Wavelet Transform (DWT)

Wavelet transform is applied in two domains namely continuous and discrete. CWT (Continuous Wavelet Transform) is the correlation between the wavelet at different scales (inverse of frequency) and the signal and is figured by changing the size of the investigation window each time, moving it, increasing it by the flag. Scientific condition is given by

$$\varphi_x(\tau,R) = \frac{1}{\sqrt{p}} \int X(t).\varphi * \left(t - \frac{\tau}{p}\right) dt \qquad (12)$$

In the above expression τ (translation) and R (scale) are variables required for transforming the signal x (t). Psi (Ψ) is the transforming function known as mother wavelet. In DWT (Discrete Wavelet Transform) a 2D signal (image) I(x, y) is first filtered through low pass and high pass finite impulse response filters (FIR), having impulse response h[n] in horizontal direction and then decimated by factor of 2. This gives first level decomposition. Further the low pass filtered image is again filtered through low pass and high pass FIR filters in vertical direction and then again decimated by 2 to obtain second level decomposition. Filtering operation is given by the convolution of the signal and impulse response of signal.

$$X[n] * h[n] = \sum_{k=-\infty}^{\infty} X[k].h[n-k] \qquad (13)$$

Now to perform inverse wavelet transform, first up sample the sub band images by factor of 2 column wise and then filter them through low pass and high pass FIR filters. Repeat the same process in next step row wise. Now add all the images to get the original image.

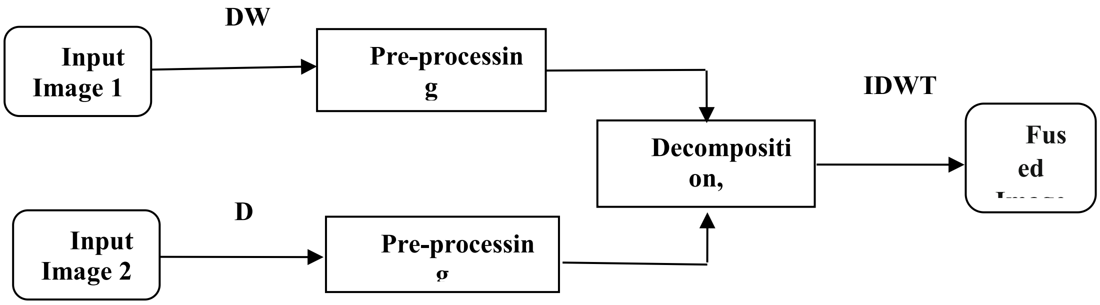



**Figure 4: Image Fusion Process of DWT**

### 3.1.3.1 Procedural steps for image fusion using DWT algorithm

1) Take the two input multimodal medical images.

2) Resize both images into 512 x 512 dimensions.

3) Convert both the images into gray scale if required.

4) Apply 2D-DWT on both the images and obtain its four components.

5) Now apply the fusion rule as per the requirement.

a) Most extreme pixel determination governs (all maximum): By choosing every single greatest coefficient of both the input images and merging them.

b) Mean: By taking the normal of the coefficients of both the images.

c) Blend: By taking the normal of the estimated coefficients of both the input images and choosing the most extreme pixels from detail coefficients of both the input data.

6) Now apply IDWT to obtain the fused output image.

### 3.1.4 Discrete cosine harmonic wavelet transforms (DCHWT)

A DCT expresses a predetermined order of data indicated in terms of a sum of cosine functions alternate at different frequencies. The discrete cosine transform generate the signal in the symmetric cyclic order and remove the discontinuity symmetric signal to move from one step to next step efficiently. The extension of the symmetric signal make the length into double for the original signal and giving better frequency resolution for factor of two.

$A_E(t)$ and $\psi_E(t)$ are denoted as real symmetric signal and real symmetric wavelet function respectively.

$$R_c(x,y) = \frac{|x|^{\frac{1}{2}}}{2\pi} \int_{-\infty}^{\infty} A_E(\sigma)\, \Psi_E(x\sigma) \cos(\sigma y)\, d\sigma \qquad (14)$$

Where the cosine transforms are represented by $A_E(\sigma)$ and $e(\sigma)$ of wavelet functions $A_E(t)$ and $\psi_E(t)$, respectively. The wavelet transform $R_c(x,y)$ used in the cosine domain moderately than the Fourier domain. Consequently, Eq. 13 can be modified as

$$R_c(x,y) = |x|^{\frac{1}{2}-1}[R_E(\sigma)\Psi_E(x\sigma)] \qquad (15)$$

In Eq.14 cosine transform functions $A_E(\sigma)$ and $e(\sigma)$ are used to compute the cosine wavelet coefficients $R_c(x,y)$ for a particular scale x. The harmonic wavelet function is denoted as $\Psi(\sigma)$ in harmonic wavelet transform, the cosine harmonic wavelet function $s(\sigma)$ is easy and it is zero for all frequencies apart from the small frequency band where it is stable, It is referred by.

$$\Psi_E(\sigma) = \Big\{ -\sigma_c - \sigma_0 < \sigma - \sigma_c + \sigma_{0,} \qquad (16)$$

The equivalent wavelet $\varphi_E(t)$ in time domain is converted into.

$$\Psi(t) = \frac{\sigma_0}{\pi} \frac{\sin \sigma_0 t}{\sigma_0 t} \cos(\sigma_c t)$$

$$= \frac{\sigma_0}{\pi} \sin c(\sigma_0 t) \cos(\sigma_c t) \qquad (17)$$

The Shannon scaling function is a cosine modulated edition of the protect wavelet. The symmetric rectangular function and for a discrete signal, it is zero apart from on symmetric finite bands [π/c, π/d] and [−π/c, −π/d] where c, d can be real numbers for the spectral weighing in cosine harmonic transform. The cosine harmonic transform too suffers from the difficulty of poor time localization and the result of spectral weighing to restrict in time period by wavelet functions other than rectangular outputs in non-orthogonal wavelets due to spectral overlap similar to the Fourier based harmonic wavelet transform. In discrete cosine harmonic wavelet transform the multimodal medical image is decomposed by cluster the discrete cosine transform coefficients in a method similar to that of discrete Fourier transform coefficients except for the conjugate procedure in inserting the coefficients symmetrically. The inverse discrete cosines transform of these collection results in discrete cosine harmonic wavelet coefficients. The discrete cosine transform of these progression subbands results in subband DCT coefficients, which are relocated in their equivalent spot to recover the overall DCT range at the unique sampling rate.

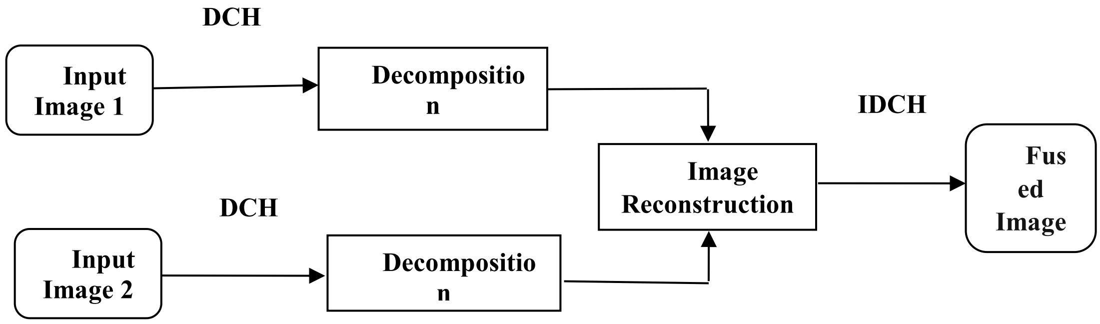



**Figure 5: Image Fusion Process of DCHWT**

### 3.1.4.1 Procedural steps for image fusion using DCHWT algorithm

1) Take the two source multimodal medical images.
2) Resize both images into 512 x 512 dimensions
3) Divide the first 2D image into rows and link them together in a chain form to have a 1D row vector R.
4) Divide the second 2D image into columns and link them together in a chain form to have a 1D column vector C.
5) Apply DCHWT on both R and C separately and then apply averaging operation on the vectors.
6) Apply inverse DCHWT on the resulting vector.
7) Convert 1D vector into 2D image to obtain the fused output medical image

### 3.1.5 Curvelet Transform Techniques

Curvelet transform method is based on medical image segmentation which divides the input multimodal medical image into number of small overlapping tiles and ridegelet transform is applied to each of the tiles to perform edge detection. The resulting fused output multimodality medical image provides more information by preventing image denoising. Curvelet transform results giving superior performance than other transform techniques in terms of signal to noise ratio value. The curvelet transform method classified into four stages such as subband decomposition, smooth partitioning, renormalization and ridgelet analysis.

### 3.1.5.1. Sub-band decomposition

The input multimodal medical image is first decomposed into wavelet sub-bands and then curvelet subbands are formed by performing partial image reconstruction from these wavelet sub-bands at various levels.

$$f \mapsto \left(P_0 f, \Delta_1 f, \Delta_2 f, \ldots\right) \tag{18}$$

Divide the multimodal medical image into resolution layers. Each layer contains details of different frequencies: P0 – Low-pass filter. $\Delta_1$, $\Delta_2$ – Band-pass (high-pass) filters

The original image can be reconstructed from the sub-bands:

$$f = P_0\left(P_0 f\right) + \sum_s \Delta_s\left(\Delta_s f\right) \tag{19}$$

Energy preservation

$$\|f\|_2^2 = \|P_0 f\|_2^2 + \sum_s \|\Delta_s f\|_2^2 \tag{20}$$

### 3.1.5.2. Smooth partitioning

The decomposed multimodal medical image each subband is smoothly windowed in to 'squares' of an appropriate scale.

$$h_Q = w_Q \cdot \Delta_s f$$

(21)

### 3.1.5.3. Renormalization

The outcome of the smoothening multimodal medical image of each resulting square is renormalized to unit scale.

(22)

### 3.1.5.4. Ridgelet analysis

$$g_Q = T_Q^{-1} h_Q$$

In the earlier two levels we transform the multimodal medical image curved lines into small straight lines. That improves the ability of the Curvelet transform to handle the medical image curved edges.

Ridgelet Transform: The Ridgelet Transform deals efficiently with line singularities in 2D. The basic idea is to map a line singularity in the two-dimensional (2D) domain into a point by means of the Radon transform. Then, a one-dimensional wavelet is performed to deal with the point singularity in the Radon domain

$$\alpha_{(Q,\lambda)} = \langle g_Q, \rho_\lambda \rangle$$

(23)

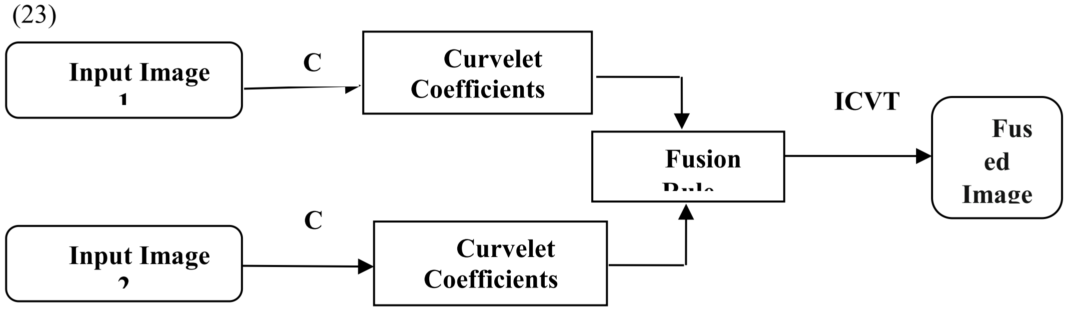



**Figure 6: Image Fusion Process of Curvelet Transform**

### 3.1.5.5 Procedural steps for image fusion using Curvelet Transform algorithm

1) Take the two input multimodal medical images.

2) Resize both images into 512 x 512 dimensions.

3) Each input multimodal medical image is then analyzed and a set of Curvelet coefficients are generated

4) Maximum Selection, Minimum Selection and Simple Average fusion rules are applied.

5) Finally apply the Inverse Curvelet transform (ICVT) to reconstruct the multimodal source image.

6) Perform the image reconstruction and get the final fused multimodal medical image.

### 3.1.6 PCNN Model

Pulse coupled neural network system (PCNN) is a novel visual cortex roused neural system portrayed by the worldwide coupling and heartbeat synchronization of neurons.

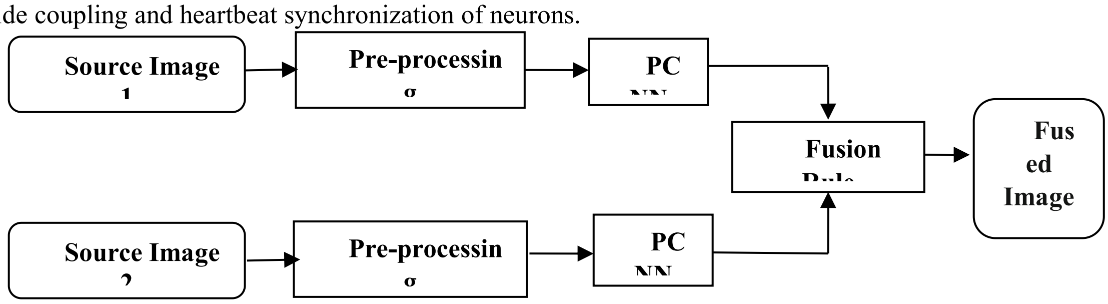



**Figure 7: Image Fusion Process of PCNN**

### 3.1.6.1 Procedural steps for image fusion using PCNN

1) Take the two input multimodal medical images.

2) Resize both images into 512 x 512 dimensions.

3) Each input multimodal medical image is then analyzed and performing pre-processing operations based on neural network fusion rule.

4) Perform segmentation operation on the pre-processed multimodality medical image with the PCNN.

5) Finally reconstruct the multimodal medical source imageand then the segmented feature objects and the original image are fused to improve the rate of object identification.

6) Perform the image reconstruction and get the final fused multimodal medical image.

### 3.1.7 Fuzzy Logic

Fuzzy image processing is not a unique theory. The collection of segments and features of fuzzy sets represent the process of fuzzy image processing. The selected fuzzy techniques are used for representation and processing of the fuzzy logic problem. It is classified into three steps:

Image fuzzification

- It is used for membership functions to graphically describe a situation

Modification of membership values

- Application of fuzzy rules

Image defuzzification

- It is obtaining the crisp or actual results

The fuzzy techniques process the coding of image data and decoding of the results are steps that make possible to process images. The membership values of the middle step modification are the major power of the fuzzy image processing. The appropriate fuzzy techniques revise the membership values after the image data are transformed from gray-level plane to the membership plane. The approach of the fuzzy integration and fuzzy rule is based on fuzzy clustering.

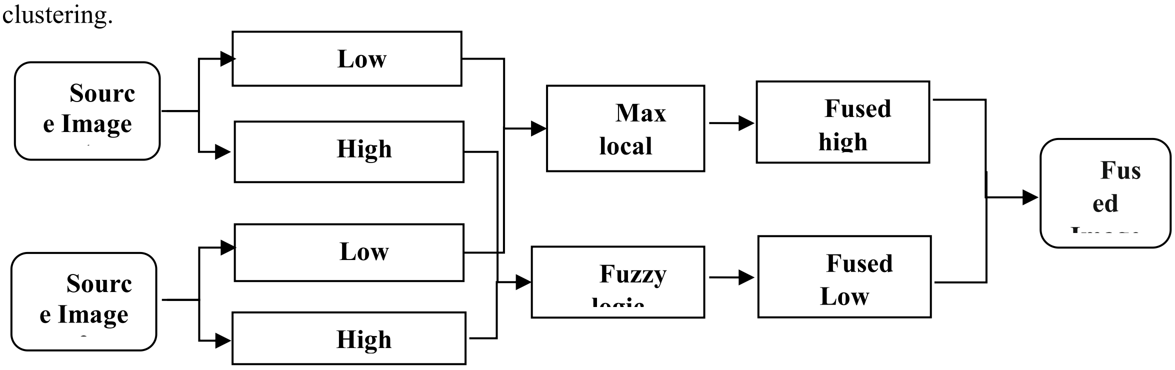



**Figure 8: Image Fusion Process of Fuzzy Logic**

After the defuzzification process the final fused multimodality therapeutic image is obtained. The algorithm for pixel-level medical image fusion using fuzzy logic is given as follows.

3.1.7.1 Procedural steps for image fusion using Fuzzy Logic.

1) Take the two input multimodal medical images Image 1 and Image 2.

2) Resize both images into 512 x 512 dimensions

3) The input images are in matrix form where each pixel gray level value is varies from 0 to 255.

4) Compare rows and columns values of input images.

5) Convert the multimodality images in column form which has C = r1×c1 entries.

6) Make a fuzzy inference system file, which has two input medical images.

7) Decide number and type of membership functions for both the input multimodal medical images by tuning the membership functions.

7) Input images in antecedent are resolved to a degree of membership ranging 0 to 255.

8) Make fuzzy if-then rules for input medical images, which resolve those two antecedents to a single number from 0 to 255.

9) For num = 1 to C in steps of 1, apply fuzzification using the rules developed above on the corresponding pixel gray level values of the input multimodality medical images, which gives fuzzy sets represented by membership functions and results in output medical image in column format.

10) Convert the column form to matrix form and display the fused final multimodal medical image.

## 3.2 Hybrid Multimodal Medical Image Fusion Techniques

Traditional medical image fusion techniques lack the ability to get high-quality images. So, there is a bad need to use hybrid fusion techniques to achieve this objective. The basic idea of the hybrid technique is to combine the guided image filter fusion technique with neural network fusion techniques to improve the performance and increase fused image quality. Another possibility is applying two stage transformations on input images before fusion process. These transformations provide better characterization of input images, better handling of curved shapes and higher quality for fused details. The overall advantages of the hybrid techniques are improving the visual quality of the images, and decreasing image artifacts and noise. **Figure 9**a, 9b shows dataset 1 of original MRI and PET images. Each image size is 512*512 dimensions. **Figure 10** to 15 illustrates the schematic diagram of the proposed hybrid multimodal medical image fusion techniques.

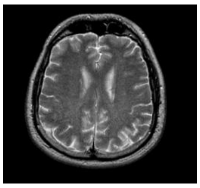


**Figure 9**(a): Original MRI image

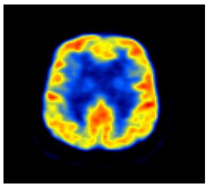


**Figure 9**(b): Original PET image

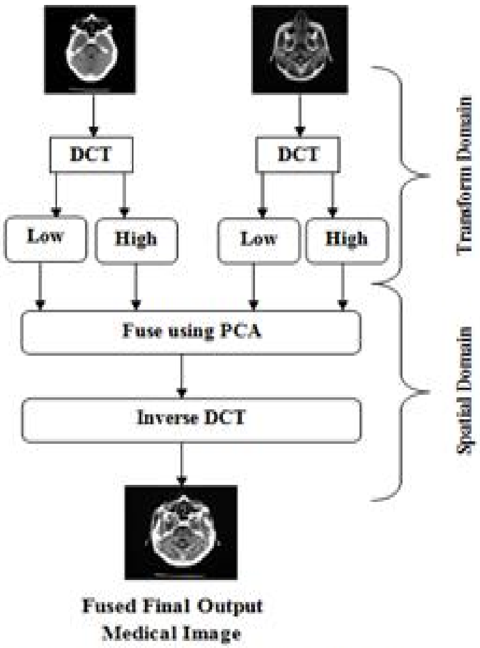



Figure 10: Proposed structure of hybrid fusion algorithm (DCT-PCA)

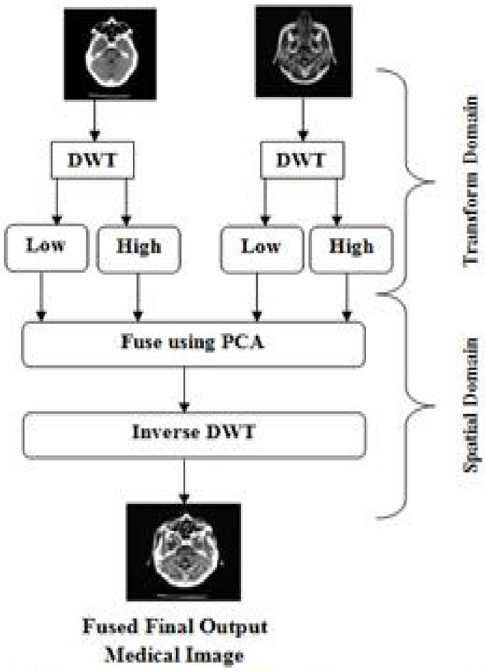



Figure 11: Proposed structure of hybrid fusion algorithm (DWT-PCA)

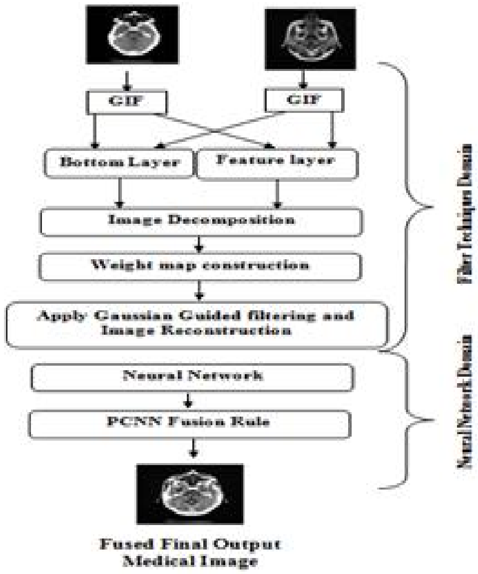



Figure 12: Proposed structure of hybrid fusion algorithm (GIF-PCNN)

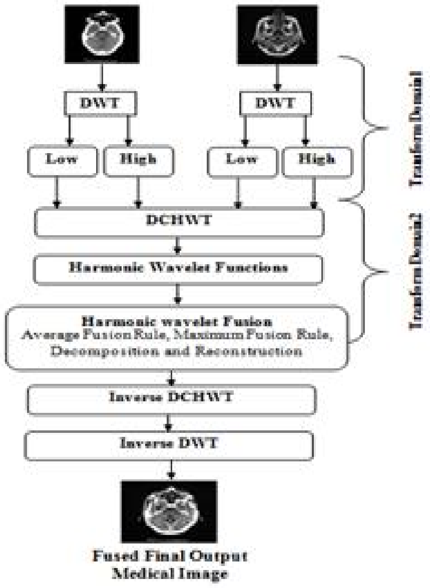



Figure 13: Proposed structure of hybrid fusion algorithm (DWT-DCHWT)

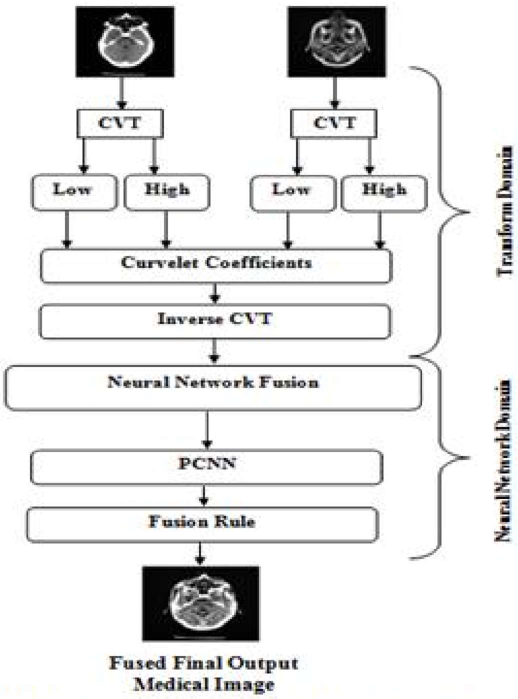



Figure 14: Proposed structure of hybrid fusion algorithm (CVT-PCNN)

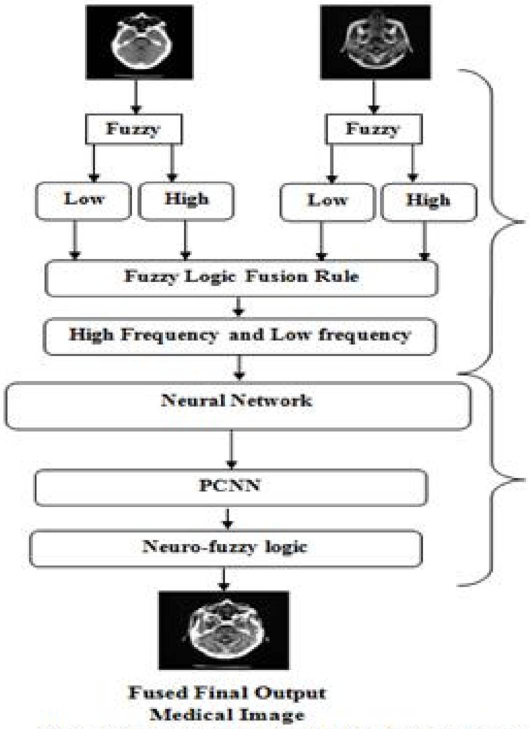



Figure 15: Proposed structure of hybrid fusion algorithm (Neuro-Fuzzy)

### 3.2.1 Proposed hybrid multimodal image fusion Algorithm (DCT-PCA)

In this work both DCT and PCA are applied on the source multimodal medical images.

Input: X and Y are the two inputs of multimodal medical images which need to be processed.

Output: Multimodality medical Image which is getting merged.

Step 1: Obtain the wavelet coefficients of the two source images.

Step 2: Alter the wavelet coefficient matrices into column vectors.

Step 3: Divide the first 2D image into rows and link them together in a chain form to have a 1D row vector R

Step 4: Divide the second 2D image into columns and link them together in a chain form to have a 1D column vector C.

Step 5: Select the eigen vector equivalent to well-built eigen value and divide its each component by mean of that eigen vector. This will give us first principal component P1. Repeat the same procedure with eigenvector corresponding to smaller eigen value to get second principal component P2. Do this for all four sets of covariance matrices.

Step 6: Multiply the normalised eigen vector values with the suitable wavelet coefficient matrix (P1 with approximate coefficient matrix of first image and P2 with approximate coefficient matrix of second image)

Step 7: Do this for both approximate and detail coefficients of both the images.

Step 8: Now apply IDCT to these manipulated coefficient matrices to rebuild the image.

Step 9: Final fused multimodal medical image is displayed.

### 3.2.2 Proposed hybrid multimodal image fusion Algorithm (DWT-PCA)

In this work both DWT and PCA are applied on the source multimodal medical images.

Input: A and B are the two inputs of multimodal medical images which need to be processed.

Output: Multimodality medical Image which is getting merged.

Step 1: Obtain the wavelet coefficients of the two source images.

Step 2: Alter the wavelet coefficient matrices into column vectors.

Step 3: Compute the covariance matrix using these vectors such that each matrix has first column vector obtained through first image and second column vector obtained through second image will give us four sets of covariance matrices.

Step 4: Form the eigen values K and eigen vectors E of the covariance matrices.

Step 5: Select the eigen vector equivalent to well-built eigen value and divide its each component by mean of that eigen vector. This will give us first principal component P1. Repeat the same procedure with eigenvector corresponding to smaller eigen value to get second principal component P2. Do this for all four sets of covariance matrices.

Step 6: Multiply the normalised eigen vector values with the suitable wavelet coefficient matrix (P1 with approximate coefficient matrix of first image and P2 with approximate coefficient matrix of second image)

Step 7: Do this for both approximate and detail coefficients of both the images.

Step 8: Now apply IDWT to these manipulated coefficient matrices to rebuild the image.

Step 9: merged output multimodal medical image is displayed.

### 3.2.3 Proposed hybrid multimodal image fusion algorithm (GIF-PCNN)

In this work both GIF and PCNN are applied on the input source multimodal medical images.

Input: X and Y are the two inputs of multimodal medical images which need to be processed.

Output: Multimodality medical image which is getting fused.

Step 1: The input source images are decomposed into multi-level representations by average filtering.

Step 2: Apply the Gaussian laplacian filtering for weight map construction.

Step 3: Perform the reconstruction operation on the both bottom layer and feature layers of different input images.

Step 4: Now apply the PCNN pre-processing steps on the guided filter processed source images.

Step 6: Apply the pulse coupled neural network fusion rule for the accurate medical image fusion.

Step 7: Fused final output multimodal medical image is displayed.

### 3.2.4 Proposed hybrid multimodal image fusion Algorithm (DWT-DCHWT)

In this work both DWT and DCHWT are applied on the source multimodal medical images.

Input: A and B are the two inputs of multimodal medical images which need to be processed.

Output: Multimodality medical Image which is getting merged.

Step 1: Obtain the wavelet coefficients of the two source multimodal medical images.

Step 2: Alter the wavelet coefficient matrices into column vectors.

Step 3: Compute the covariance matrix using these vectors such that each matrix has first column vector obtained through first image and second column vector obtained through second image will give us four sets of covariance matrices.

Step 4: Form the eigen values K and eigen vectors E of the covariance matrices.

Step 5: Divide the first 2D image into rows and link them together in a chain form to have a 1D row vector R.

Step 6: Divide the second 2D image into columns and link them together in a chain form to have a 1D column vector C.

Step 7: Do this for both approximate and detail coefficients of both the images.

Step 8: Apply inverse DWT and DCHWT on both source images separately and then apply averaging operation on the vectors. .

Step 9: Fused output multimodal medical image is displayed.

### 3.2.5 Proposed hybrid multimodal image fusion algorithm (CVT-PCNN)

In this proposed research work applied both Curvelet Transform and PCNN techniques on the input source multimodal medical images.

Input: CT/MRI and PET/SPECT are the two inputs of multimodal medical images which need to be processed.

Output: Multimodality medical image which is getting fused.

Step 1: The input source multimodal medical images are registered and analyzed then set of Curvelet coefficients are generated.

Step 2: Maximum Selection, Minimum Selection and Simple Average fusion rules are applied.

Step 3: Perform the reconstruction operation on the both bottom layer and feature layers of different input images.

Step 4: Now apply the Inverse Curvelet transform (ICVT) to reconstruct the multimodal source image.

Step 6: Apply the pulse coupled neural network fusion rule for the accurate medical image fusion.

Step 7: Fused final output multimodal medical image is displayed.

### 3.2.6 Proposed hybrid multimodal image fusion Algorithm for (Neuro Fuzzy logic)

In this work both Fuzzy Logic and PCNN are applied on the input multimodal medical images.

Input: I1 and I2 are the two inputs of multimodal medical images which need to be processed.

Output: Multimodality medical image which is getting fused.

Step 1: Take the two input multimodal medical images I1 and I2.

Step 2: Resize both images into 512 x 512 dimensions

Step3: Variables I1 and I2 are multimodal images in matrix form where each pixel gray level value is in the range from 0 to 255.

Step4: Compare rows and columns of both input multimodal medical images.

Step5: Convert the multimodality images in column form which has $C = r1\times c1$ entries.

Step6: Make a fuzzy inference system file, which has two input medical images.

Step7: Decide number and type of membership functions for both the input multimodal medical images by tuning the membership functions.

Step 8: Input images in antecedent are resolved to a degree of membership ranging 0 to 255.

Step 9: Make fuzzy if-then rules for input medical images, which resolve those two antecedents to a single number from 0 to 255.

Step 10 : For num = 1 to C in steps of 1, apply fuzzification using the rules developed above on the corresponding pixel gray level values of the input multimodality medical images, which gives fuzzy sets represented by membership functions and results in output medical image in column format.

Step11: Apply the pulse coupled neural network fusion rule with fuzzy logic for the accurate medical image fusion.

Step 12: Convert the column form to matrix form and display the fused final multimodal medical image. Membership functions and rules used in the Neuro-fuzzy system

## 4 Evaluation Metrics

Fusion quality metrics are utilized in this work to evaluate the efficiency of the fusion algorithms. These metrics are:

## 4.1 Average Gradient (g)

The average gradient represents the amount of texture variation in the image. It is calculated as:

$$g = \frac{1}{(R-1)(S-1)} \sum_{i=1}^{(R-1)(S-1)} \frac{\sqrt{(\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial x})^2}}{2} \tag{16}$$

Where, R and S are the image dimensions of images x and y respectively.

## 4.2 Standard Deviation (STD)

It is used to establish how much difference of the data is from the average or mean value. The input data is said to be clearer if its STD value is bigger. STD is deliberate using the equation:

$$STD = \frac{\sqrt{\sum_{i=1}^{R} \sum_{j=1}^{S} |f(i,j) - \mu|^2}}{RS} \tag{17}$$

Where R and S represent the dimensions of the image f(i,j), and the mean value is represented by $\mu$ .

## 4.3 Local Contrast ($C_{local}$)

It is an index for the image quality and purity of view. It is calculated using the equation:

$$C_{local} = \frac{|\mu_{target} - \mu_{background}|}{\mu_{target} + \mu_{background}} \tag{18}$$

Where $\mu_{target}$ is the mean gray-level of the target image in the local region of interest and $\mu_{background}$ is the mean of the background in the same region. The larger value of C indicates more purity of the image.

## 4.4 Structural Similarity Index Metric (SSIM)

It is a measure of the similarity between two regions $w_x$and $w_y$of two images x and y.

$$SSIM(x,y|w) = \frac{(2\bar{w}_x\bar{w}_y + C_1)(2\sigma w_x w_y + c_2)}{(\bar{w}_x{}^2 + \bar{w}_y{}^2 + C_1)(\sigma^2 w_x + \sigma^2 w_y + c_2)} \tag{19}$$

Where, $C_1$ and$C_2$ are small constants.$\bar{w}_x$ ,$\bar{w}_y$ are the mean values of $w_x$and $w_y$. $\sigma^2 w_x$ , $\sigma^2 w_y$ are the variance of $w_x$and $w_y$. $\sigma w_x w_y$ is the covariance between the two regions

## 4.5 Xydeas and Petrovic Metric ($Q^{AB/F}$)

This metric is used to measure the transferred edge information amount from source images to the fused one. A normalized weighted performance form of that metric can be calculated as following

$$Q^{AB/F} = \frac{\sum_{m=1}^{M} \sum_{n=1}^{N} (Q_{(m,n)}^{AF} W_{(m,n)}^{AF} + Q_{(m,n)}^{BF} W_{(m,n)}^{BF})}{\sum_{m=1}^{M} \sum_{n=1}^{N} W_{(m,n)}^{AF} + W_{(m,n)}^{BF}} \tag{20}$$

Where, $Q_{(m,n)}^{AF}$,$Q_{(m,n)}^{BF}$ is the edge information preservation value and $W_{(m,n)}^{AF}$,$W_{(m,n)}^{BF}$ are their weights

## 4.6 Mutual Information (MI)

MI is an index that calculates the quantity of dependency between two images (R, S), and it gives the joint distribution detachment between them using the subsequent equation:

$$I(r,s) = \sum_{y \epsilon R} \sum_{r \epsilon R} p(r,s) \log\left(\frac{p(r,s)}{p(r)p(s)}\right) \tag{21}$$

Where p(r) and p(s) are the marginal probability distribution functions of the both images, and p(r,s) is the joint probability distribution function.

$$MI(r,s,f) = \frac{I(r,s) + I(r,f)}{H(r) + H(s)} \tag{22}$$

Where, H(r), H(s) are the entropies of images r and s.

## 4.7 Feature Similarity Index Metric (FSIM)

It represents edge similarity between input images and the fused image, and it can be calculated from the following equation:

$$FSIM = \frac{\sum_{x \in \Omega} S_L(x).PC_m(x)}{\sum_{x \in \Omega} PC_m(x)} \tag{23}$$

Where, the image spatial domain is Ω, the total similarity between the two images is $S_L$ (x), and the phase congruency value is $PC_m(x)$.

### 4.8 Edge Intensity (S)

A higher edge intensity of an image represents a higher image quality and more clearness. Edge intensity for image f can be measured using Sobel operator (S).

$$Sx = f * hx\,, Sy = f * hy \qquad (24)$$

$$\sqrt{(s_x{}^2 + s_y{}^2)} \qquad (25)$$

Where $h_x = \begin{pmatrix} -2 & 0 & 2 \end{pmatrix}$ , $h_y = \begin{pmatrix} 0 & 0 & 0 \end{pmatrix}$ (26)

### 4.9 Image Entropy (E)

It is a measure of the amount of information contained in the image, and it takes values from 0 to 8, and it can be defined as:

$$E = -\sum_{i=0}^{n} p(x_i) \log p\,(x_i) \qquad (27)$$

Where $x_i$of the $i^{th}$ point is its gray-scale value and is its probability. It is said that the image is better if it has a large value of E.

### 4.10 Universal Image Quality Index (UIQI)

UIQI is a quality based metric that measures the correlation between two images x and y using the following equation:

$$Q_0(x,y) = \frac{\delta xy}{\delta x \delta y} \cdot \frac{2\bar{x}\bar{y}}{\bar{x}^2+\bar{y}^2} \cdot \frac{2\delta x \delta y}{\delta x^2+\delta y^2} \qquad (28)$$

Where $\bar{x},\bar{y}$ is the mean value of an image x, y. $\delta x^2$ , $\delta y^2$ is the variance of image x, y. $\delta xy$ is the covariance between x and y.

### 4.11 Peak Signal-to-Noise Ratio (PSNR)

It is a quantitative measure based on the Root Mean Square Error (RMSE), and it is calculated as:

$$PSNR = 10 \text{ x } \log\left(\frac{(fmx)^2}{RMSE^2}\right) \qquad (29)$$

Where $f_{max}$ represents the maximum pixel gray level value in the reconstructed image.

### 4.12 Processing Time

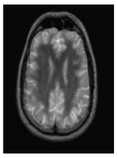
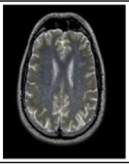
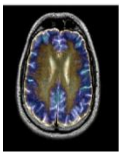
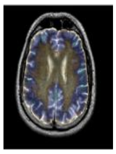
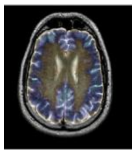
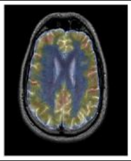
It represents the time required for the fusion process in seconds according to the computer specifications.

## 5 Experimental Results and Discussions

The implementations are based on two stages. Firstly, the traditional fusion algorithms are applied to datasets of MRI and PET images and evaluated using all metrics mentioned in the previous section. The implementation is executed in MATLAB R2015b on windows 7 laptop with Intel Core I5 Processor, 4.0 GB RAM and 500 GB Hard Disk. The processed multimodality therapeutic input images are gathered from harvard medical school [27] and radiopedia.org [28] medical image online database. The size of the image is 512 × 512 for execution process. Table 1 shows the experimental results of the different traditional medical image fusion algorithms on dataset 1.

Table1. Performance Metrics obtained for different traditional medical image fusion algorithms

| Method | Metrics | PCA | DWT | DCHWT | CVT | GIF | PCNN | FUZZY |
|---|---|---|---|---|---|---|---|---|
| Dataset 1 | AG | 0.0389 | 0.0645 | 0.0682 | 0.0907 | 1.0671 | 1.0982 | 0.0386 |
| | STD | 0.0026 | 0.0029 | 0.0031 | 0.0035 | 0.3161 | 0.3854 | 0.0019 |
| | $C_{local}$ | 0.6962 | 0.7829 | 1.0842 | 1.2941 | 1.3821 | 0.6852 | 0.7015 |
| | SSIM | 0.9547 | 0.9613 | 0.9645 | 0.9662 | 0.9686 | 0.9712 | 0.9589 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $Q^{AB/F}$ | 0.2581 | 0.3434 | 0.2863 | 0.2163 | 0.3472 | 0.4173 | 0.2312 |
| | MI | 0.6521 | 0.7269 | 0.6729 | 0.4729 | 0.5739 | 0.7957 | 0.5942 |
| | FSIM | 0.9261 | 0.9317 | 0.9517 | 0.9158 | 0.9672 | 0.9879 | 0.9478 |
| | EI | 0.3923 | 0.4173 | 0.4632 | 0.4891 | 0.5132 | 0.5321 | 0.3871 |
| | IE | 7.4810 | 7.5182 | 7.6271 | 7.6513 | 7.6941 | 7.9835 | 7.8421 |
| | UIQI | 0.7427 | 0.7521 | 0.7531 | 0.7639 | 0.7763 | 0.7954 | 0.6543 |
| | PSNR | 64.17 | 65.18 | 64.43 | 36.23 | 41.41 | 34.12 | 64.87 |
| | PT | 2.671 sec | 2.598 sec | 2.931 sec | 3.523 sec | 3.123 sec | 2.412 sec | 3.173 sec |
| | Fused Image |  |  |  |  |  |  |  |

From the previous table, it is clear that:

1) The PCNN fusion algorithm introduces the highest average gradient, edge intensity, and standard deviationvalues because of the isotropy and directionality property that enhances the representation of curves and edgesleading to fused images with much details and much more clearness. Also, curvelet fusion has better averagegradient, edge intensity, and standard deviation values than the other algorithms.

2) The curvelet fusion algorithm introduces the highest local contrast values, because curvel*et al*gorithm is basedon Ridgelet transform, which divides a curve into a number (n) of lines. The dual tree fusion algorithm also hasbetter local contrast values than the other algorithms as it improves directionality using 12 directional wavelets. On the other hand, the PCNN has low local contrast because of the isotropy and directionality property thatdeals with all directions collectively leading to loss of clarity.

3) The CVT and DWT achieve the best edge information transferred from source images to the fused onerepresented by $Q^{ab/f}$metric. Also, the PCNN has a good $Q^{ab/f}$ value.

4) In the fusion process, a new image of new properties is produced. So, perfect similarities between the inputimages and the fused one are not preferred. The PCNN and curvelet present lower similarities with input images.

5) The GIF and DWT have the highest mutual information with input images representing more dependency onthe input images.

6) The GIF achieves the highest correlation between the MR and the fused images. The PCNN has the highestcorrelation between the PET and fused images represented in the universal image quality index.

7) The PSNR is based on the RMSE between input and fused images. Hence, lower PSNR and higher RMSE arepreferred for good fusion. The PCNN and curvelet fusion introduce the lowest PSNR values.

8) All algorithms introduce good entropy results.

9) The processing time required for fusion with the PCNN is the lowest but curvelet fusion has the longest time.Also, the Fuzzy consumes longer time than the other algorithms.

10) Visual inspection ensures that the overall enhancement in the fused images using curvel*et al*gorithm is betterthan that of the PCNN algorithm. Also GIF introduces a good enhancement.

# In summary:

The PCNN has a superior performance followed by the curvelet except for local contrast that reduces purity of view in the case of the PCNN algorithm.

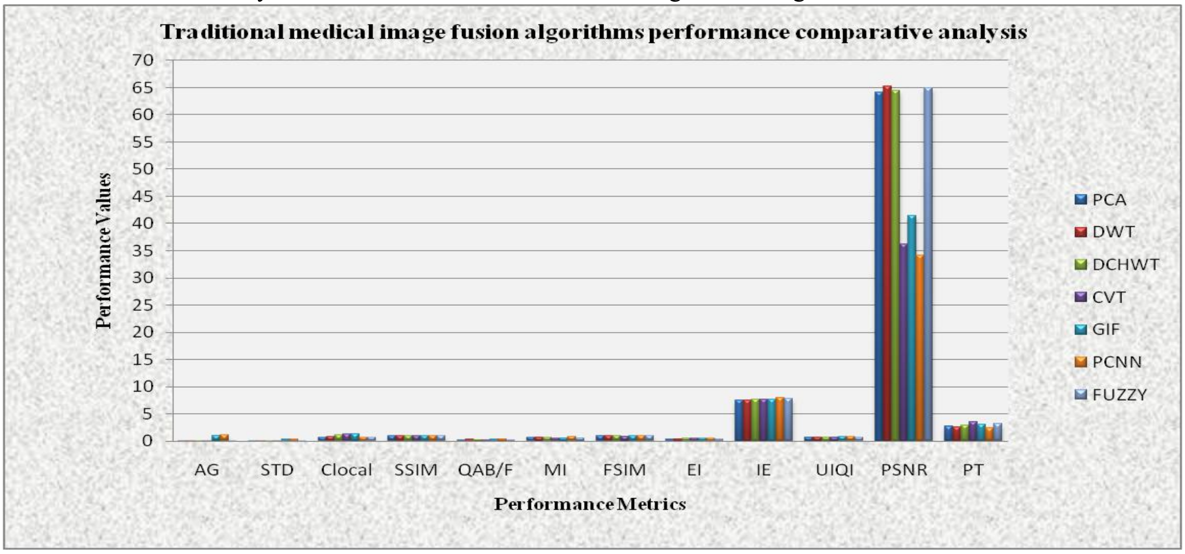
Curvelet fusion has a better performance than the other algorithms except for the processing time that is verylong.

GIF has a good performance with short processing time, good local contrast, and average gradient.

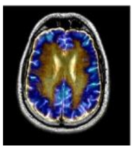
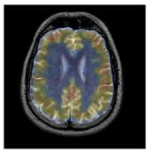
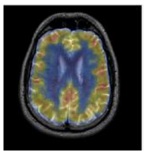
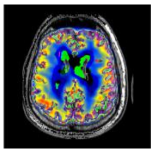
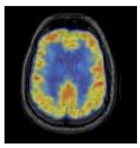
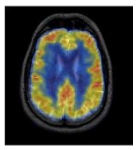
PCA and fuzzy have the worst performance compared to the other algorithms.

Increasing the number of pixels of the input images increases the processing time, dataset 1.On the other hand, lower size images decrease the time, data-set 1.

We could make use of hybrid transforms that combine advantages of all algorithms.




Secondly, the hybrid fusion algorithms are applied to datasets of CT, MRI, PET and SPECT images and evaluated. Six combination techniques are implemented in this section: (PCA+DWT), (PCA + DCT), (DCHWT + DWT), (Curvelet + PCNN),

| Method | Metrics | PCA+DWT | PCA+DCT | DCHWT+ DWT | CVT+ PCNN | GIF+ PCNN | FUZZY+ PCNN |
|---|---|---|---|---|---|---|---|
| Dataset 1 | AG | 0.0362 | 0.0368 | 0.0375 | 0.0762 | 0.0681 | 0.0823 |
| | STD | 0.0010 | 0.0015 | 0.0031 | 0.0024 | 0.0035 | 0.0042 |
| | $C_{local}$ 保 | 0.6413 | 0.6624 | 0.6831 | 1.1451 | 0.9863 | 1.2310 |
| | SSIM | 0.9654 | 0.9742 | 0.9645 | 0.9834 | 0.9823 | 0.9963 |
| | $Q^{AB/F}$ | 0.2510 | 0.0996 | 0.2412 | 0.2512 | 0.2612 | 0.2732 |
| | MI | 0.5621 | 0.5319 | 0.5721 | 0.5831 | 0.5925 | 0.6012 |
| | FSIM | 0.9312 | 0.9338 | 0.9481 | 0.9532 | 0.9641 | 0.9715 |
| | EI | 0.3451 | 0.7012 | 0.3512 | 0.6932 | 0.3998 | 0.7150 |
| | IE | 7.669 | 7.781 | 7.472 | 7.741 | 7.841 | 7.932 |
| | UIQI | 0.5312 | 0.2321 | 0.3214 | 0.4123 | 0.5131 | 0.5921 |
| | PSNR | 64.06 | 59.12 | 58.01 | 60.12 | 57.12 | 55.16 |
| | PT | 3.752 sec | 3.417 sec | 2.781 sec | 2.891 sec | 3.131 sec | 1.671 sec |
| | Fused Image |  |  |  |  |  |  |

From the previous table, it is clear that:

1) The (PCNN + Fuzzy) hybrid fusion technique introduces the highest average gradient, local contrast, edge intensity, and standard deviation values. Also the (GIF + PCNN) hybrid technique has better performance than the other hybrid techniques.

2) All hybrid techniques provide good entropy values close to 8.

3) The (DWT + Curvelet) has the lowest structural similarity and PSNR, but (DCHWT+DWT) has the lowest feature similarity.

4) For UIQI metric, mutual information, and $Q^{ab/f}$ the (PCA + DWT) has the worst values representing poor edge information transferred to the fused images. This can be shown obviously through the visual inspection. The Curvelet with PCNN, GIF-PCNN, and Fuzzy-PCNN provide better values.

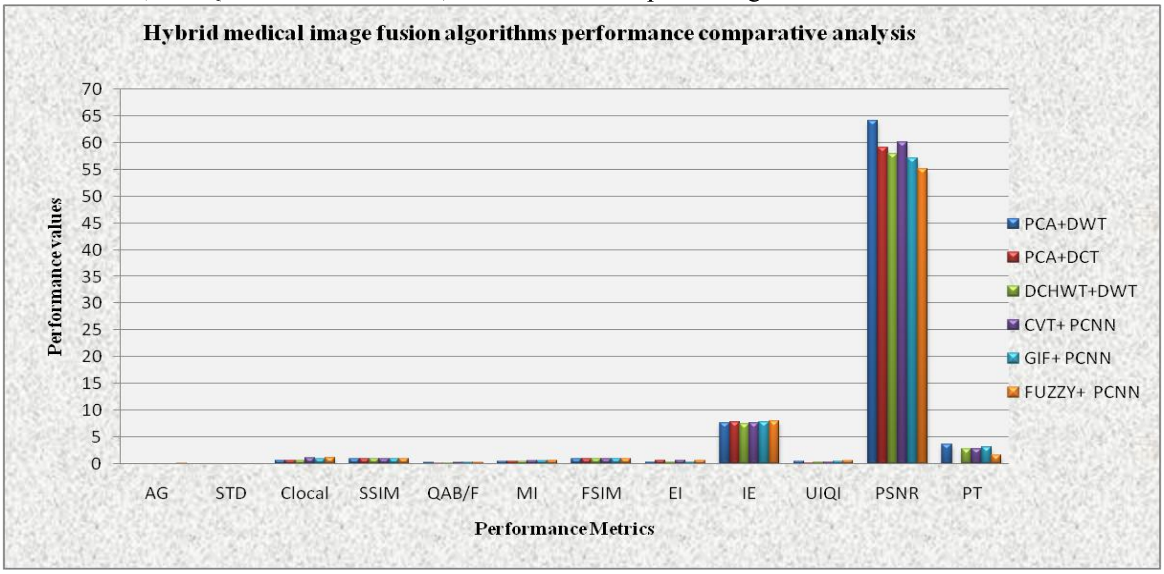
5) The processing time for (CVT+PCNN) is still the longest time; however the (PCNN + Fuzzy) has the shortest

consumed time.

In summary

(Neuro + Fuzzy) has a superior performance except for UIQI factor, mutual information, and $Q^{ab/f}$ unfortunately; this reduces edge information and causes pixelization. Also, it has a very long processing time.

The (GIF + Fuzzy and CVT + Fuzzy) has a better performance than the other hybrid techniques with the best UIQI, mutual information, and $Q^{ab/f}$ values. Moreover, it has the shortest processing time.




# 6. Conclusion

This paper examines the performance of both the traditional and hybrid multimodal medical image fusion techniques using some evaluation metrics. It has been exposed that the best multimodality medical image fusion technique implemented was the hybrid algorithm. This hybrid method introduced a better performance compared to traditional algorithms. It gives much more image details, higher image quality, the shortest processing time, and a better visual inspection. All these advantages make it a good choice for several applications such as medical disease analysis for an accurate treatment. Compared with other existing techniques the proposed technique experimental results demonstrate the better processing performance and results in both subjective and objective evaluation criteria.

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