# A THESIS REPORT
# ON

# MRI/PET IMAGE FUSION USING MULTIWAVELET TRANSFORM

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# CERTIFICATE

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Certifies that this report titled **‘MRI/PET Image fusion ’** is a bonafide record of the project submitted by **Princy Sindhu (2K13/SPD/14**) towards the partial fulfillment of the of the requirements for the award of the degree of **Master of Technology in Signal Processing & Digital Design, Electronics & Communication Engineering of the DELHI TECHNOLOGICAL UNIVERSITY.**

**GUIDE**
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# ABSTRACT

Image fusion is the technique of blending multiple images to obtain a fused image with more descriptive and reliable information. The keen motivation behind image fusion is to compound the complementary as well as relevant information of several images captured from a common scene, to generate an image comprising the superior features of source images. With the availability of modern instrumentation (medical imaging tools) and developed technologies, medical image fusion has become a vital tool in medical applications. Medical image fusion is a concept dealing with the idea of improving the image content by fusion of multiple images obtained using various imaging tools such as Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Computed Tomography (CT), Single photon Emission Computed Tomography (SPECT). The objective of this project work is to develop a novel fusion algorithm to fuse two different modality images of brain of a patient to obtain a resulting image with more clear view and complete description. In this work, a framework for medical image fusion based on Multi-Wavelet transform is proposed. Multi-Wavelet transform is improvement over traditional scalar wavelet. In the first part of project work, PET and MRI images are aligned with each other. In the second part, two images are decomposed using Discrete Multi-wavelet transform. In third part of work, these decomposition coefficients are merged correspondingly using edge detection method. In fourth part of work, using these new coefficients, inverse wavelet transform is applied to obtain a fused image with better human/machine perception. Several data set for different diseases are experimented on.

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# CHAPTER 1

# INTRODUCTION

## 1.1 Overview

Image Fusion is basically an emerging technique of blending the important and complementary information of multiple images without any loss of information [1], [2]. Various input images either in same domain or various domains are merged together to develop an image containing the larger, relevant, reliable and consistent information in comparison to all input images in a single fused image [3]. The resultant fused image will be more informative, accurate, descriptive and complete than the original source images [4]. The basic idea behind image fusion is to integrate low detail multisensor images captured from a common scene to obtain a fused (hybrid) image with a high spatial resolution multispectral image [5]. It is an efficient approach of extracting the more informative values from a set of images. It effectively increases the spatial and spectral resolution optimality. Image fusion is also an effective way to reduce the increasing volume of information by representing the useful and descriptive information from multimodal source images in a single image only. With rapid improvement in various domain of imaging technologies and modern instrumentation, multisensory system has become a reality in various applications such as machine vision, military applications, high speed object tracking, automatic vehicular systems, remote sensing, medical imaging etc. With such advancement in real time applications, Image fusion has proved itself as an efficient and powerful tool to increase the human and machine perception and to decrease the storage space requirement minimizing the cost [6].

Medical image fusion is a rapidly developing and emerging application of image fusion to handle various medical issues retrieved from multimodal medical images. Medical image fusion is the process of combining multiple images from single or multiple imaging tools with significant information into a single image that retains the useful information and describes the scene better. Medical image fusion helps in increasing the reliability of images and decreasing the redundancy and storage cost. It increases the quality and provides a clear visual effect of medical images for the diagnosis, analysis, treatment of medical problems, and for historical documentation [7]. This technique has gained a vital importance in tumor diagnosis in brain, mouth, breast etc . For fusion process in medical image fusion, multiple image acquisition can be done using a common source or using different imaging modalities. Medical image fusion using two or more imaging tools is known as multimodal medical image fusion. Medical image fusion is basically a concept of improving the image content and quality by merging images captured from different imaging tools as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), SPCET, X-ray, DST etc . All the above mentioned tools provide the images with different spectral features. In case of clinical diagnosis, use of single image is not the sufficient requirement for the physician. Thus for the sake of accuracy in diagnosis, more than one image with different and complementary features are fused together. This eliminates the limitation of diagnosis using single sensor image.

Figure 1.1 shows the three major focused areas of studies in medical image fusion: (a) identification, improvement and development of imaging modalities useful for medical image fusion, (b) development of different techniques for medical image fusion, and (c) application of medical image fusion for studying human organs of interest in assessments of medical conditions.

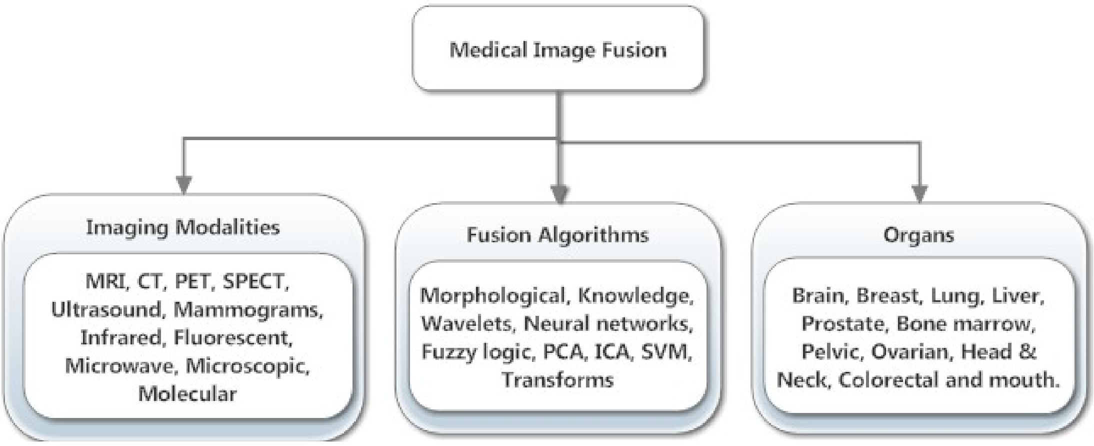



Fig. 1.1. A chart showing the nature of modalities, methods and organs of interest as applied in medical image fusion studies.

Medical images from different modalities tools will have different geometric representation. For fusion process, images for fusion should be in same geometric representation. Thus image pre-processing is the first and important need of the medical image fusion, in which images are transformed into a common representation, retaining the best resolution of each sensor. The alignment of multisensor images (multisensor images registration) is process of image pre-processing while fusing different multiple images. When multiple input images for fusion are captured from multiple different sensors, is known as multisensory system. When single sensor images are used for fusion, a sequence of images is captured for fusion and each image is fused together, representing the consistency in images. Depending on features and quantity of sensors, sensor system may be single sensor fusion system and multisensory fusion system [6]. Image fusion should be shift and rotational invariant, means it should not be affected by the change in location and orientation.

### 1.2 Single Sensor Fusion System

Fig 1.2 represents single sensor image fusion. In image fusion using single sensor, a sequence of images is processed and fused together generating a new fused image with optimum and descriptive information content. Sensors used in single Sensor Fusion System may be visible band Sensor or matching band Sensor. The system is applicable in condition of poor illumination, noisy environment (fog, smoke, rain), varying climatic conditions etc. where resultant fused image clearly describes the scene and helps in object detection efficiently. System has some drawbacks depending on limiting features of the imaging sensors employed such as limited focal length, operating conditions, the dynamic range, resolution, etc. For example, a visible-band sensor (such as digital camera) can efficiently work in daylight scene with high illumination but is not suitable for night scene or under adverse conditions such as in fog, smoke or rain having poor illumination.

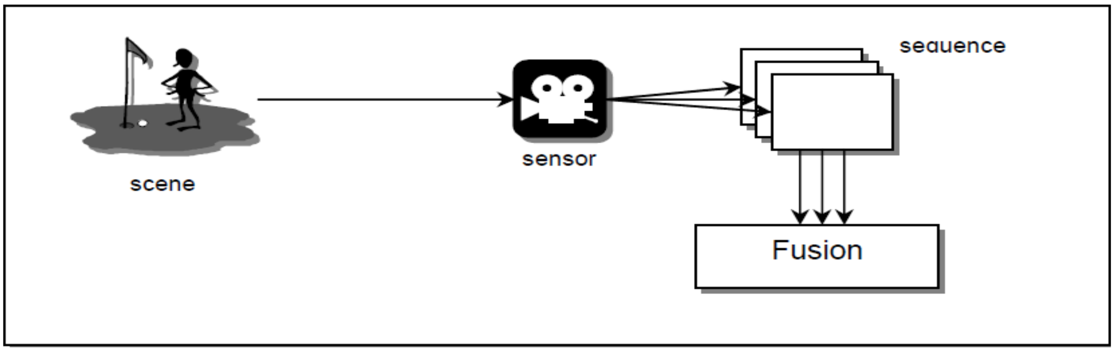



Fig 1.2 Single Sensor Image Fusion Systems

### 1.3 Multisensory Image Fusion System

A multi-sensory image fusion system is a scheme employed with multiple sensors for image acquisition from a common scene. Basic idea behind its increasing applicability is blending of the relevant and complementary visual information from multiple images with variable geometric representations. It develops a single resultant image without any information loss, increased reliability and consistency. Sensors used in the System are such as complementing each other and enhancing the quality of captured images by single sensor. Figure 1.3 shows a multi-sensor image fusion system representing the fusion of individual images collected by an infrared camera accompanied by the digital camera. Both Sensors complements each other and overcomes the issues of single sensor system. Infrared Camera operates efficiently in poor illumination and adverse conditions. Thus it can complement vision band Camera that can work only in high illumination and enhance the application of the System.

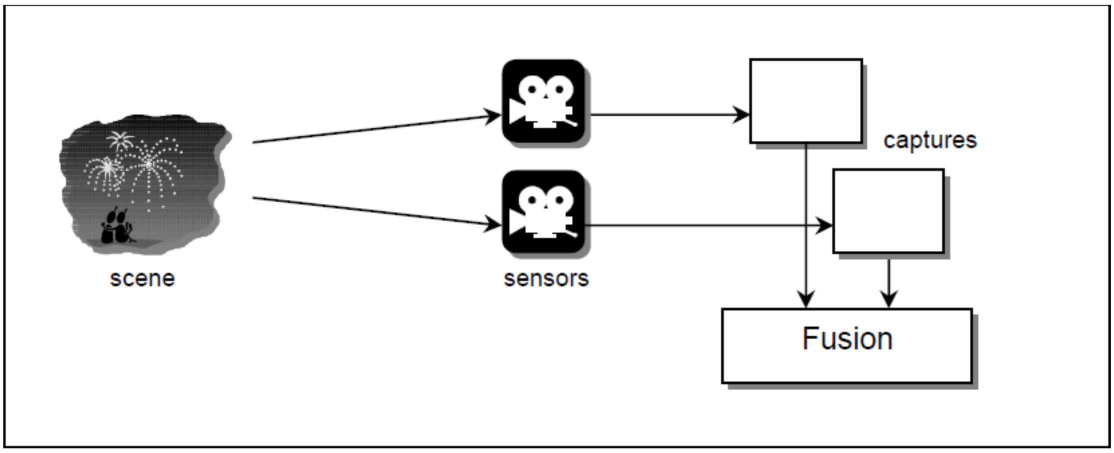



Fig 1.3. Multisensory image fusion system

Multisensory fusion system is beneficiary over single sensor image fusion system in terms of improved reliability, increased system performance, reduced ambiguity, less storage space, increased system robustness and extended spectral and spatial coverage.

### 1.4 Levels of Medical Image Fusion

Depending on the merging state or abstraction level, medical image fusion should be performed at three levels [8], [9], [10]:-

1.4.1 Pixel level fusion: -

It is the lowest level of fusion also known as Signal level fusion. Pixel level fusion deals with the information associated with each pixel in source image and generate a fused image with the corresponding pixel values depending on certain rules and method. It can be performed at both spatial and frequency domain. It is conducted for contrast reduction.

1.4.2 Feature level fusion: -

Feature level fusion deals with property descriptive information, already been extracted from the source images such as pixel intensities, edge and texture. These extracted features and object labels are fused to obtain the fused medical image with additional composite features. It is also known as object level fusion and is applicable for object detection or classification.

1.4.3 Decision level fusion: -

Decision level Fusion is the highest level fusion or symbol level image fusion which represents fusion of probabilistic decision information. It deals with the decision obtained by local decision-makers operating on the results of feature level processing on image data produced from individual sensors.

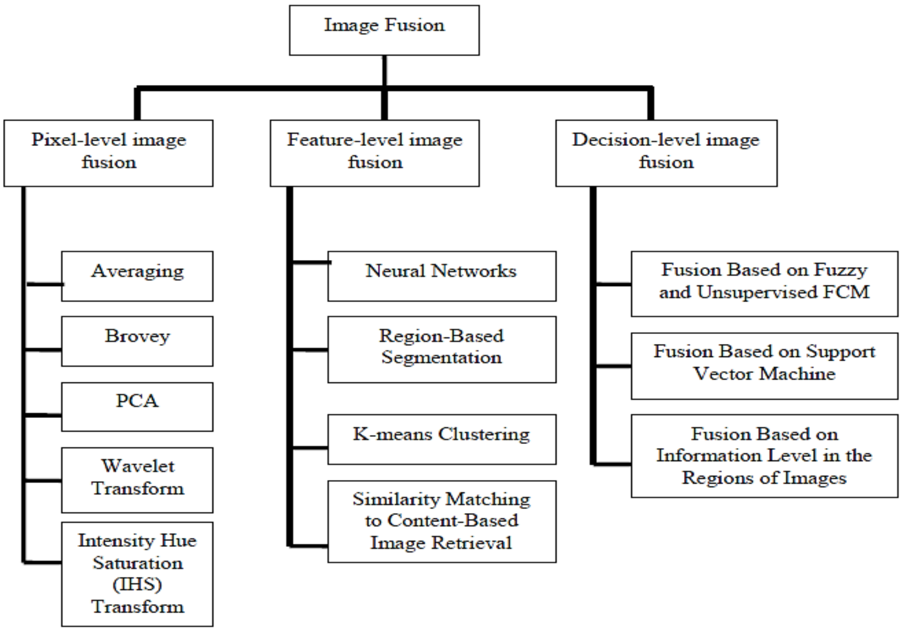



Fig 1.4. Image fusion methods, level classification

Figure 1.4 represents the classification of most popular image fusion methods depending on the level of computation and abstraction of the source images. The bottom branches show the typical image fusion algorithms that fall into each fusion level. The pixel-level method works either in the spatial domain or in the transform domain. Feature-level algorithms typically segment the image into contiguous regions and fuse the regions using their properties. Decision-level fusion algorithms combine image descriptions to fuse.

## 1.5 Image Pre-processing

Figure 1.5 represents the pre-processing steps used in Medical image fusion. Pre-processing steps include image registration, image resampling and image fusion. In case of multimodal or multisensor image fusion, input images may vary in their spatial alignment. First step in fusion process is the spatial alignment of multimodality input images, image registration [11], [12]. The registration of the images is a method to correct the spatial misalignment between the different image data sets that often involve compensation of variability resulting from scale changes, rotations, and translations. The misalignment of image features is induced by various factors including the geometries of the sensors, different spatial positions and temporal capture rates of the sensors and the inherent misalignment of the sensing elements. The problem of registration becomes complicated in the presence of inter-image noise, missing features and outliers in the images. Registration technique is necessary in order to be able to compare or integrate the data obtained from different measurements. It align the images by exploiting the similarities between sensor images. The mismatch of image features in multisensor images reduces the similarities between the images and makes it difficult to establish the correspondence between the images. Image fusion is the combination of extracted features in common spatial alignment and evaluated with specific method.

Input Images

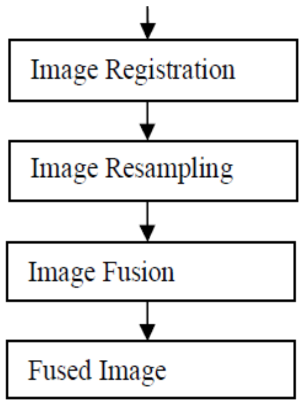



Fig 1.5 Pre-processing steps for image fusion

**1.6 Medical image fusion methods: -**

Methods used for image fusion broadly lies in two category depending upon the domain in which they are processed.

**1.6.1 Spatial Domain Method: -**

These are the techniques in which each input image is processed pixel-by-pixel directly. Images are modulated in the same time domain of retrieval. Averaging, maximum value, minimum value, PCA, Intensity-Hue-Saturation method, Brovery Transform is some of the techniques used as Spatial Domain method.

a. Simple Averaging method: -

This is the simplest technique for fusion which is based on higher pixel intensity value. In this technique, two images are fused by taking average of the intensity value and focus on maximum intensity. Let X(x,y) and Y(x,y) are two input images to be fused. Intensity value of each pixel is added and divided by 2 to take the average of their intensities.

$$F(x,y)=(X(x,y)+Y(x,y))/2$$

where F(x,y) is the fused image.

b. Maximum or Minimum Selection technique: -

In this technique, images are fused in order to maximize the focus of image. Each pixel of the output fused image is assigned with the maximum or minimum intensity value.

$$P(i,j) = \sum_{i=0}^{m} \sum_{j=0}^{n} \max X(i,j) Y(i,j)$$

$$P(i,j) = \sum_{i=0}^{m} \sum_{j=0}^{n} \min X(i,j) Y(i,j)$$

where P(i,j) is the fused image obtained.

c. Intensity-hue-Saturation based Fusion: -

This is an efficient technique to fuse panchromatic (PAN) image with multispectral (MS) image [13]. Also an efficient tool used for fusion in remote sensing. In this fusion method, any RGB image is first converted to Intensity-Hue-Saturation image. Intensity component of the HIS domain preserves the largest description of the image. This intensity component is replaced or modulated according to the high resolution PAN image giving an intensity image as output. Using previous Hue and Saturation component, new intensity component is converted back to RGB image which represents a fused image. Fast HIS and IKONOS based Fusion are the modified technique in which processing speed is increased preserving the spectral characteristics.

d. PCA based fusion: -

Principal Component Analysis [14] is a mathematical method in which correlated components are processed to transforms into uncorrelated components. This technique is used to compress the multidimensional data to low dimensional data set and ideally describe the data. Uncorrelated components obtained are also known as Principal components. First principal component has the largest variance and contains the maximum image information which is common to all subbands. Second component is perpendicular to the first and third component is perpendicular to the first two components. This is an efficient tool to merge PAN and MS image but at the expense of color information.

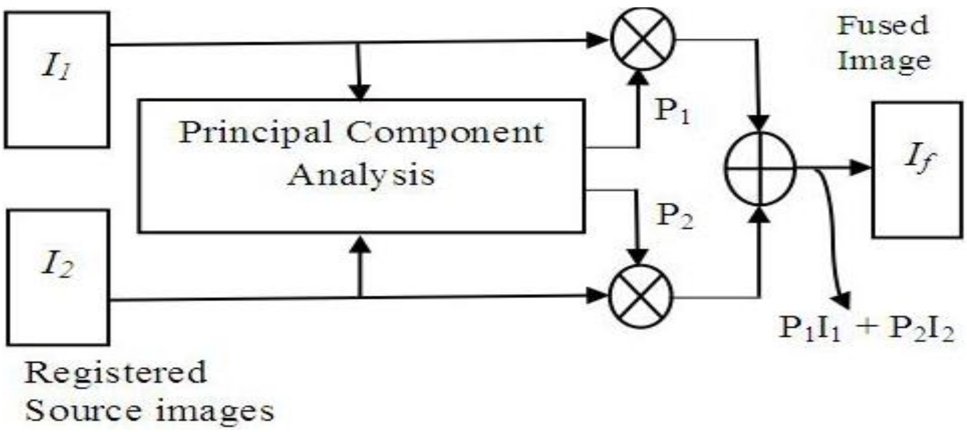



Fig.1.6. Image Fusion using PCA

The diagram here represents the Fusion scheme using PCA. In this technique $P_1$ and $P_2$ are the first principal components for the two images respectively. Fused image is obtained by the following formula: -

$$I_f = P_1I_1+P_2I_2$$

Where $I_1$ and $I_2$ are the two input images for Fusion and $I_f$ is the fused image output obtained using PCA technique.

**2. Transform Domain Method: -**

The method of fusion in which input image is processed in its frequency domain. Original image in time domain is first transformed into another domain using wavelet transform, curvelet tansform, contourlet transform, framelet transform, shearlet transform etc. Different frequency component subbands are then fused using any fusion technique.

a. Laplacian Pyramid Method:-

In this technique, image is represented in number of levels known as pyramid. These pyramids are fused together by checking the consistency of each image. The more descriptive part from two images is retained in the fused pyramid and other is eliminated. Using these fused pyramid and inverse pyramid transform, fused image is obtained.

b. Wavelet Transform:-

Wavelet Transform is a powerful mathematical tool to represent a time domain data in time-frequency localization. Conventional Fourier transform is the transformation process used to convert a signal from time domain to frequency domain. Wavelet Transform is improved version of Fourier transform and overcome its limitations. It is a noticeable and highly efficient method which overrides the conventional Fourier transform in image processing. The reason behind its success is its ability to process non-stationary signals with transitory phenomena [15],[16]. Wavelet transform depends on two functions: one scaling function and one wavelet function. Scaling function is known as father wavelet and Wavelet function is known as mother wavelet. Its decomposition components are known as daughter wavelet which preserves the whole characteristics of mother wavelet. Due to single scaling and wavelet function, Wavelet Transform has some limitations in time-frequency localization. These limitations are eliminated by the development of DWT, DWT-CT, and MultiWavelet Transform. These all technique decomposes the image input into more number of subbands. These subbands will provide the vertical, 2 directional and horizontal information of the image.

c. Contourlet Transform: -

It is the improved technique over wavelet transform having directionality and anisotropy properties. Holding these properties, it can efficiently eliminate noise from 2D image signal in which Wavelet decomposition lacks. It is the cascade system of Laplacian Pyramid and directional filter bank (DFB). It have basis functions at various direction that provides it the directionality property. The figure represents the design of Contourlet Transform. The input image is divided into 4 frequency subbands Low-Low subband (LL), bandpass subband (LH, HL and HH). LL here is the approximation coefficient which is passed through laplacian pyramid where it is further divided. Division is preformed until fine details of the image are not obtained. Its performance is limited due to high computational complexity and lack of exact continuum theory for this concept.

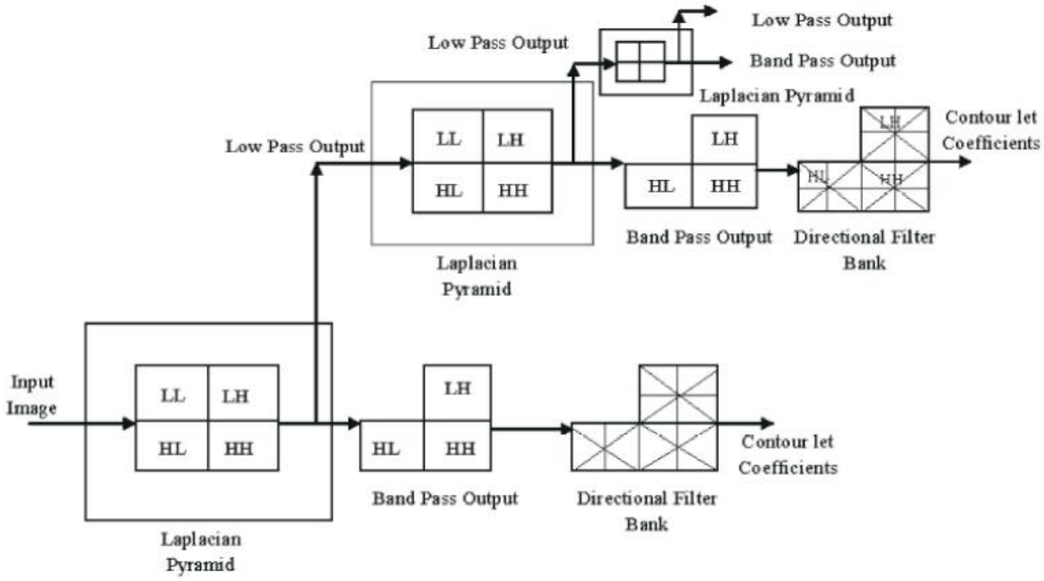



Fig.1.7. Contourlet Transform design

d. Framelet transform: -

Framelet transform is also similar to scalar wavelet, but only difference lies in number of functions. This wavelet technique supports one scaling function and two wavelet function given by equations as : -

$$\phi(t) = \sqrt{2}\sum_n h_0(n)\phi(2t-n),$$
$$\psi_i(t) = \sqrt{2}\sum_n h_i(n)\phi(2t-n), \quad i = 1,2.$$

where $h_0(n)$ is low pass filter coefficient and $h_1(n)$ and $h_2(n)$ are the two high pass filter coefficients.

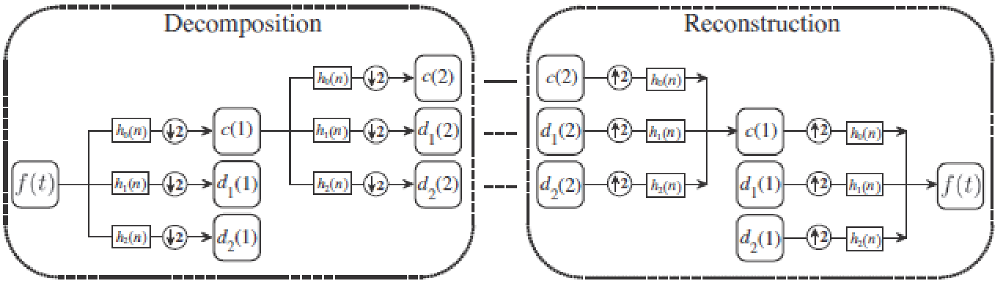



Fig.1.8. Decomposition and reconstruction in Framelet transform

The diagram represensts the decomposition and reconstruction structure of Framelet Transform. It also possess the multilevel structure, thus decomposition can be extended to multiple dimensions. Number of level depends on the number of data points in data set and is selected in the way to eliminate the noise.

e. Shearlet Transform: -

A better MSD tool developed for efficiently used in medical image fusion. It is mathematically more powerful tool than wavelet, curvelet and contourlet transform as it decomposes into more high pass subbands than other. This technique captures more directional information. Shearlet Transform mainly consists of two steps. First step is the Laplacian Pyramid filter which is performs the multiscale partitioning of the image. Second step is the directional localization with the help of pseudo-spherical Fourier Transform. Shearlets have some remarkable features: a simple mathematical structure obtained from the affine system theory, provide optimally sparse representations, and the directionality is controlled by shear matrices are used rather than rotations for controlling directionality and enables a unified continuum framework.

## 1.7 **Multimodal Medical images**: -

With the advancement in technology and medical imaging tools, medical imaging has become an emerging domain in medical diagnosis and analysis. Varieties of imaging methods are available in the medical field each possessing a different characteristic property. Various medical imaging method includes Magnetic Resonance Imaging(MRI), Computed Tomography(CT), Positron Emission Tomography(PET), SPCET etc. The complementary properties of two or more modality medical images are combined together developing a single image consisting of fine details of each image. This is known as multimodal medical image fusion.

1. CT: -

CT images are very clear for bone imaging, and they has relatively low contrast for soft tissue. X-rays are used for this imaging tool. Its main advantage is high resolution and short scan times. Nature of X-ray probe, number of X-rays generated and restriction on slices scanned, limits the performance of CT scan.

2. MRI: -

MRI is a non-invasive type of imaging technique and is efficiently used in brain diagnosis. These images can provide better information of the pathological soft tissue and the relevant vessel. This is used to efficiently extract the abnormal region present in brain representing the presence of reflective brain tumor. It is also used for imaging of soft tissues of eyes and heart with high accuracy as it does not emerge any radiation and is not harm the body. One more reason of its advantage is that it is safe for pregnant lady and its baby. Its limitation lies in its sensitivity for movement which makes it inefficient for detecting tumor in moving organs.

3. PET: -

PET is efficient tool for nuclear imaging. It can provide better information on blood flow with low spatial resolution. Its function is based on the operation of positrons. Due to molecular imaging, it possesses high sensitivity. It is used for the brain diagnosis and treatment.

4. SPECT: -

Single Photon Emission Computed Tomography is the powerful tool for nuclear imaging. It shows the blood flow to various organs in human body. It is efficiently used for brain diagnosis, lung cancer detection, neck and head cancer detection, multimodality fusion etc. It possess poor image quality as is affected by image noise and it requires post processing to enhance the image quality.

5. Ultrasound: -

Ultrasound technique is a sonar based technique. It uses Ultrasonic sound waves for the diagnosis purpose. This technique is widely used in medical applications due to its safe behaviour and low cost. Its limitation lies in operator reasons such as no air gap should be present in between body and ultrasound probe. Also there should not present any bone structure between the path of the organ under diagnosis area and probe. Ultrasound is mainly used in diagnosis in maternity cases as it has no side effects to the patient and baby.

As each modality image have some different properties. Two or more medical image when fused together will reduce the redundancy and provide accurate diagnosis result. This eliminates the risk of wrong analysis and treatment, enhancing the medical domain achievements.

### 1.8. Motivation of Medical Image Fusion: -

With contemporary development in the imaging technology and instrumentation, Image fusion has evolved as a powerful tool to enhance the features of the image, improving its quality and making it more clear and descriptive. Complementary information from two images is combined for accurate detection of any object in automatic vehicular system. Using the specific quality of each image and combining provides the surety of correct diagnosis in medical assessment. To detect any obstacle, hazardous weapon, and high speed object detection can be carried out with great efficiency using image fusion. for detecting air line track in adverse climatic condition, tracking the path by vehicles in rain and fog, for automatic machine and robotics, image fusion has played a vital role and has proved itself a foremost need for human machine perception. The main motivation behind the medical image fusion is

1. Better Diagnosis of disease
2. Reducing storage space
3. Making clinical instruments more effective
4. Enabling distant assessment accurate and effective
5. Enhancing the information content in a single image only.

# CHAPTER 2

## Literature Survey

A tremendous work has been done in the field of medical image fusion using wavelets. Wavelets provide a better result and accuracy in medical image fusion. Traditional wavelet decomposes the image using mother wavelet and father wavelet. Wavelet Transform can process non stationary signals and represent the signal in time-frequency domain that makes it superior than Fourier transform. Wavelet transform uses low pass filters and high pass filters for decomposition into approximation and detail coefficients. Traditional wavelet transform decomposes the signal into two frequency subbands only. They support single scaling function and single wavelet function. Due to presence of single scaling and wavelet function, there are some limits in time-frequency localization and redundancy in representation. To overcome this limitation, 2D-Discrete Wavelet Transform is developed, that is efficiently used in image processing for Fusion, Deblurring, denoising, and Compression. For decomposition, Image is passed through low pass filter and high pass filter. Output of both the filter is further decomposed using filter pair. Low pass filter provides the approximation coefficient and high pass filter deals with detail coefficient. It can be extended to further level in which image is decomposed till a fine detail is acquired. Here image is decomposed into number of subbands depending on the level and degree of decomposition. An image is divided into four frequency subbands in single level: LL, LH, HL and HH where L represents low frequency and H represents High frequency part. LL is the approximation coefficient and retains maximum information. LH, HL and HH are detail coefficients and represent diagonal

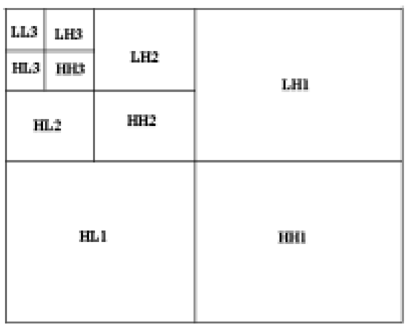



Fig.2.1. multilevel 2D DWT Decomposition

and horizontal part of the image. When LL subband is divided further into four subbands, it is second level decomposition. In this way, image can be decomposed using multilevel 2D-

DWT Transform. Approximation coefficient provides the most relevant and descriptive information used to extract features.

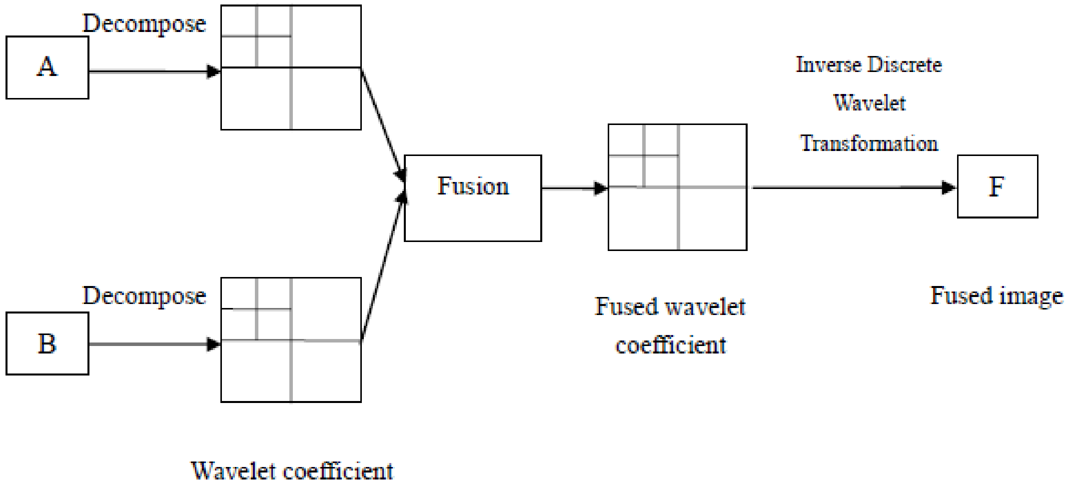



Fig.2.2.Image Fusion using 2D-DWT Method

A new paradigm added in wavelet is Multiwavelet transform. It is an extension to scalar wavelet having more than one scaling and wavelet function. Multi-Wavelet has some enhancing properties such as short support, orthogonality and symmetry. But its response is limited due to the requirement of prefiltering and postfiltering. Prefiltering here is used to convert the matrix data into vector form which is reversed back at the output using postfiltering. Many researchers are working to develop a method to override this problem. With the decomposition using more scaling and wavelet function would decompose the image into 16 subbands which increases the efficiency of fusion process providing more information at a single level. MultiWavelet transform can also be extended to multilevel and also can be enhanced using more scaling and wavelet function. To the date, MutliWavelet with 2 scaling function and 2 wavelet function has been developed. GHM, CL, and biorthogonal MultiWavelets are some of the MultiWavelets has been developed now.

# CHAPTER 3

## MultiWavelet Transform and Fusion

### 3.1. Overview: -

MultiWavelet Transform is an efficient technique for fusion process and highly applicable in remote sensing, image denoising, medical imaging, image compression etc. This polynomial wavelet is constructed by Alpert. It is an extension and more advantageous over Scalar Wavelet transforms. Scalar Wavelet Transform have some time frequency localization limitation due to the presence of only two functions: one scaling function and one wavelet function. Multi-Wavelet transform contains two or more scaling and wavelet function. For Scalar wavelet, r=1, whereas for the Multi-wavelet decomposition r>1. With increase in functions, it overcomes the limitation in wavelet due to time frequency localization problem. In comparison with scalar wavelet, Multiwavelet has the following advantages:-

a) short support
b) smoothness
c) orthogonality
d) symmetry
e) improved compression ratio

Above four advantages are the characteristics required for the accurate image processing and analysis. Multiwavelet Transform does not possess any division restriction on low and high pass filter. Commonly used Multiwavelet Transforms are GHM, CL, and biorthogonal Multiwavelet (such as BIGHM). In our project, we are using GHM Multiwavelet technique.

### 3.2. Preliminaries: -

MultiWavelet Transform is very much similar to scalar wavelet in terms of multiresolution analysis. Wavelet Transform with r=1, have single scalar function and single wavelet function, but when multiplicity r>1, Transform will support r scaling function and r wavelet function. r scaling function $\Phi_1, \Phi_2, \ldots, \Phi_r$ and r wavelet function $\Psi_1, \Psi_2, \ldots, \Psi_r$ are represented in vector form as following:

$$\Phi=(\Phi_1, \ldots,\Phi_r);$$

$\Psi=(\Psi_1,\ldots,\Psi_r)$;

These vectors satisfy the Matrix Refinement Equations (MRE), representing the multiscaling and multiwavelet functions as

$$\Phi(t) = \sqrt{2}\sum_{k=-\infty}^{k=\infty} H_k \Phi(mt-k)$$

$$\Psi(t) = \sqrt{2}\sum_{k=-\infty}^{k=\infty} G_k \Psi(mt-k)$$

$H_k$ and $G_k$ are the low pass filter matrix and high pass filter matrix respectively of r*r size. At present, most the MultiWavelet are developed with r=2 only. For r=2, H and G are 2*2 multifilter matrix.

With multiplicity r=2, 2 scaling and 2 wavelet functions, MultiWavelet Transform decomposes the input image into 16 subbands as given in the diagram. $L_xL_y$ is the approximation coefficient containing the most of the information. $L_xH_y$ , $H_xL_y$ and $H_xH_y$ are the detail coefficients representing the diagonal and horizontal properties of the image. At same level of decomposition, MultiWavelet decomposition splits an image into large number of subbands in comparison to DWT. Thus it proves more efficient for Fusion process as more data is being fused with more subbands.

| | | | |
|---|---|---|---|
| $L_1L_1$ | $L_1L_2$ | $L_1H_1$ | $L_1H_2$ |
| $L_2L_1$ | $L_2L_2$ | $L_2H_1$ | $L_2H_2$ |
| $H_1L_1$ | $H_1L_2$ | $H_1H_1$ | $H_1H_2$ |
| $H_2L_1$ | $H_2L_2$ | $H_2H_1$ | $H_2H_2$ |

Fig.3.1 Subbands of Multiwavelet Decomposition

### 3.3. MultiWavelet filter bank: -

Figure represents the scalar multifilter bank system as Multiple inputs and Multiple outputs (MIMO) system having multiplicity r. As the r output vector stream of such system with multiple inputs is the convolution of the r input stream with the r*r matrix of filter impulse response (P). Figure b represents the equivalent system that replaces multifilter bank system P with the cascade of multiplexer (MUX), r scalar filters $p_1$, $p_2$, …, $p_r$ with the downsamplers. r scalar filters in equivalent filter bank are polyphases of multifilter (P).

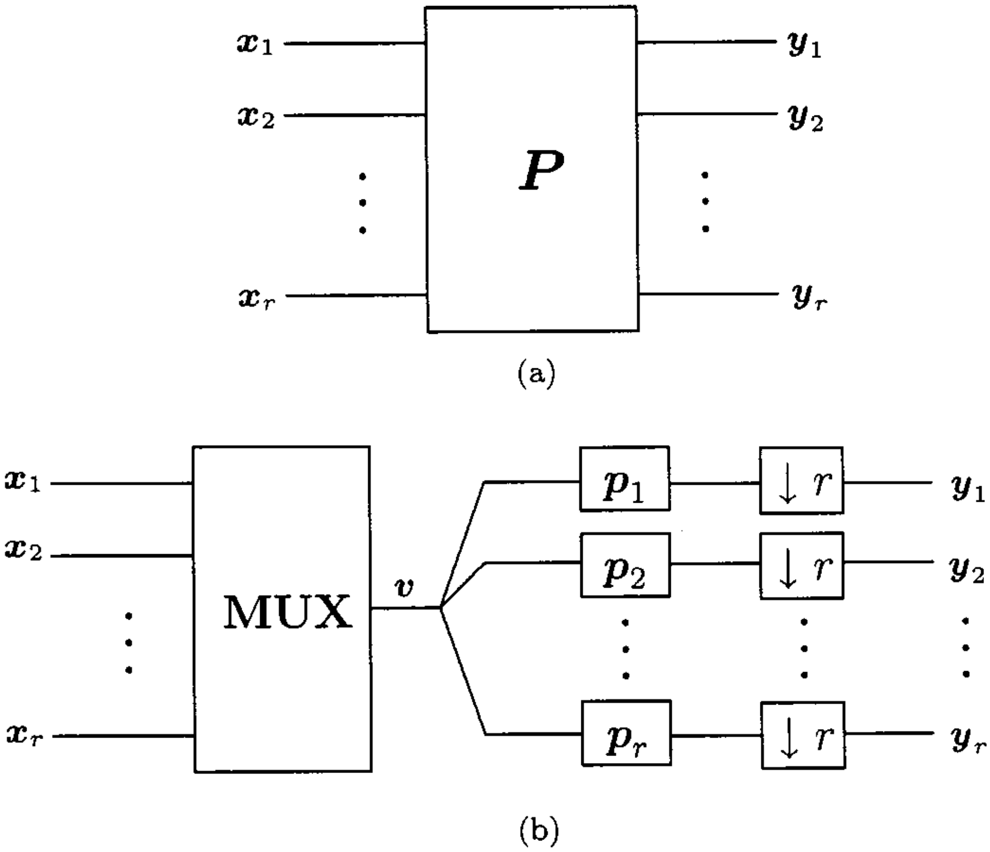



Fig.3.2 (a) Multiwavelet filter bank(multiplicity is r) (b) Equivalent filter bank(multiplicity is r) with MUX and downsamplers

Consider the MIMO system for multiwavelet transform with multiple outputs. Here the output vector stream is obtained by convolution of multiple input vector streams with the impulse transfer function (P).

$$y_k(n) = \sum_{l \in Z} \sum_{m=1}^{r} p_{k,m}(l) x_m(n-l)$$

where n ϵ Z and k=1, 2,…, r. As MUX is a multiple input and single output (MISO) operator, it will convert the multiple input streams to single stream. This filters the input data stream v using r scalar filters $p_k = (p_k(n))_{n \in Z}$ where k=1,2,…,r followed by the downsamplers with decimation factor r. Output stream obtained by the system is given as

$$y_k(n) = \sum_{\ell\in\mathbb{Z}} p_k(\ell)v(rn-\ell)$$
$$= \sum_{\ell\in\mathbb{Z}} \sum_{m=0}^{r-1} p_k(\ell r+m)v(rn-(\ell r+m)), \quad n \in \mathbb{Z}.$$

comparing above two equations, relationship between P and equivalent scalar filter system with downsamplers can be seen as

1. Multiplexer system which converts the multiple input stream into single vector stream can be obtained as

$$\mathbf{MUX} : (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_r) \mapsto \mathbf{v} : x_m(k) \to v(rk-(m-1)).$$

2. The multiplier system(P) relates with the equivalent filter bank system as

$$p_k(\ell r + m - 1) = p_{k,m}(\ell), \quad \ell \in \mathbb{Z}, \quad k, m = 1, 2, \ldots, r.$$

This equation clearly elaborate that any M channel multiwavelet system with multiplicity r can efficiently represented by M systems of scalar filter. These equivalent scalar filters comprises r polyphases of the multipier (P).

**3.4. GHM and CL**: - A multiwavelet system with 2 scaling function and 2 wavelet function is developed by J. Geronimo, D. Hardin, and P. Massopust. They have constructed this multiscaling function with fractal interpolation. For multiplicity equal to 2, these equations represent the 2 scaling functions and 2 wavelet functions of GHM.

$$\left\{ \begin{aligned} \Phi(t) = \begin{bmatrix} \varphi_1(t) \\ \varphi_2(t) \end{bmatrix} = \quad & H_0\Phi(2t) + H_1\Phi(2t-1) \\ & + H_2\Phi(2t-2) + H_3\Phi(2t-3) \end{aligned} \right\}$$

$$\left\{ \begin{aligned} \Psi(t) = \begin{bmatrix} \psi_1(t) \\ \psi_2(t) \end{bmatrix} = \quad & G_0\Phi(2t) + G_1\Phi(2t-1) \\ & + G_2\Phi(2t-2) + G_3\Phi(2t-3) \end{aligned} \right\}$$

where H are the lowpass filter matrix and G are the high pass filter matrix. Low pass filter coefficients and high pass filter coefficients are given below as

$$H_0=\begin{bmatrix} 3/5 & 4\sqrt{2}/5 \\ -1/10\sqrt{2} & -3/10 \end{bmatrix}, \quad H_1=\begin{bmatrix} 3/10 & 0 \\ 9\sqrt{2}/40 & 1/2 \end{bmatrix}$$

$$H_2=\begin{bmatrix} 0 & 0 \\ 9\sqrt{2}/40 & -3/20 \end{bmatrix}, \quad H_3=\begin{bmatrix} 0 & 0 \\ -\sqrt{2}/40 & 0 \end{bmatrix}$$

$$G_0=\begin{bmatrix} 3/10 & 2\sqrt{2}/5 \\ -\sqrt{2}/40 & -3/20 \end{bmatrix} \quad G_1=\begin{bmatrix} 3/10 & 2\sqrt{2}/5 \\ -\sqrt{2}/40 & -3/20 \end{bmatrix}$$

$$G_2=\begin{bmatrix} 3/10 & 2\sqrt{2}/5 \\ -\sqrt{2}/40 & -3/20 \end{bmatrix} \quad G_3=\begin{bmatrix} 3/10 & 2\sqrt{2}/5 \\ -\sqrt{2}/40 & -3/20 \end{bmatrix}$$

GHM has second order approximation. Its scaling function possesses short support, symmetry, and orthogonal property while wavelet function possesses symmetric/antisymmetric property. Graphical representation of GHM scaling function and wavelet function are shown as

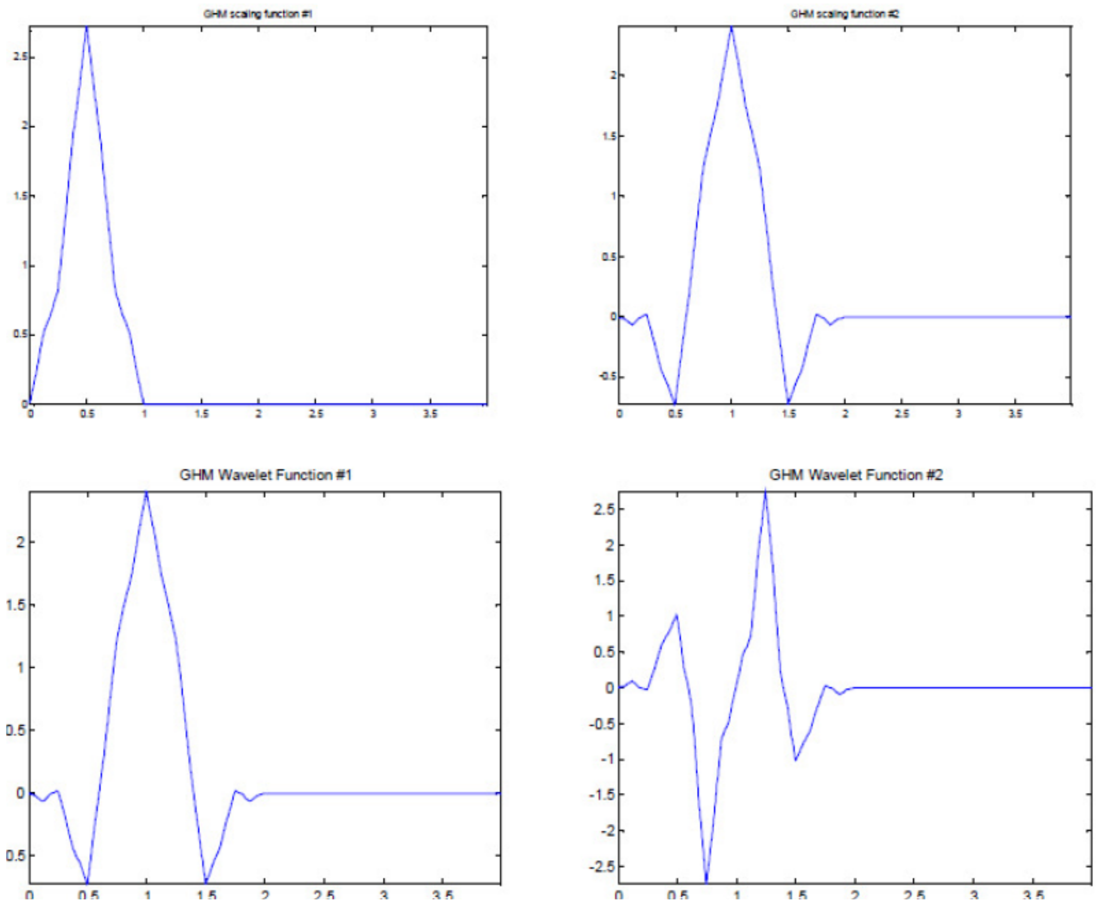



Fig.3.3 GHM scaling and wavelet function, graphical representation

CL is the multiwavelet with multiplicity r. Its low pass filter coefficients and high pass coefficients are given as

$$H_0=\begin{bmatrix} 1/4 & 1/4 \\ -\sqrt{7}/8 & -\sqrt{7}/8 \end{bmatrix} \qquad H_1=\begin{bmatrix} 1/2 & 0 \\ 0 & 1/4 \end{bmatrix} \qquad H_2=\begin{bmatrix} 1/4 & -1/4 \\ -\sqrt{7}/8 & -\sqrt{7}/8 \end{bmatrix}$$

$$G_0=\begin{bmatrix} -1/4 & -1/4 \\ 1/8 & 1/8 \end{bmatrix} \qquad G_1=\begin{bmatrix} 1/2 & 0 \\ 0 & \sqrt{7}/20 \end{bmatrix} \qquad G_2=\begin{bmatrix} -1/4 & 1/4 \\ -1/8 & 1/8 \end{bmatrix}$$

Scaling function and wavelet function of CL are graphically represented as

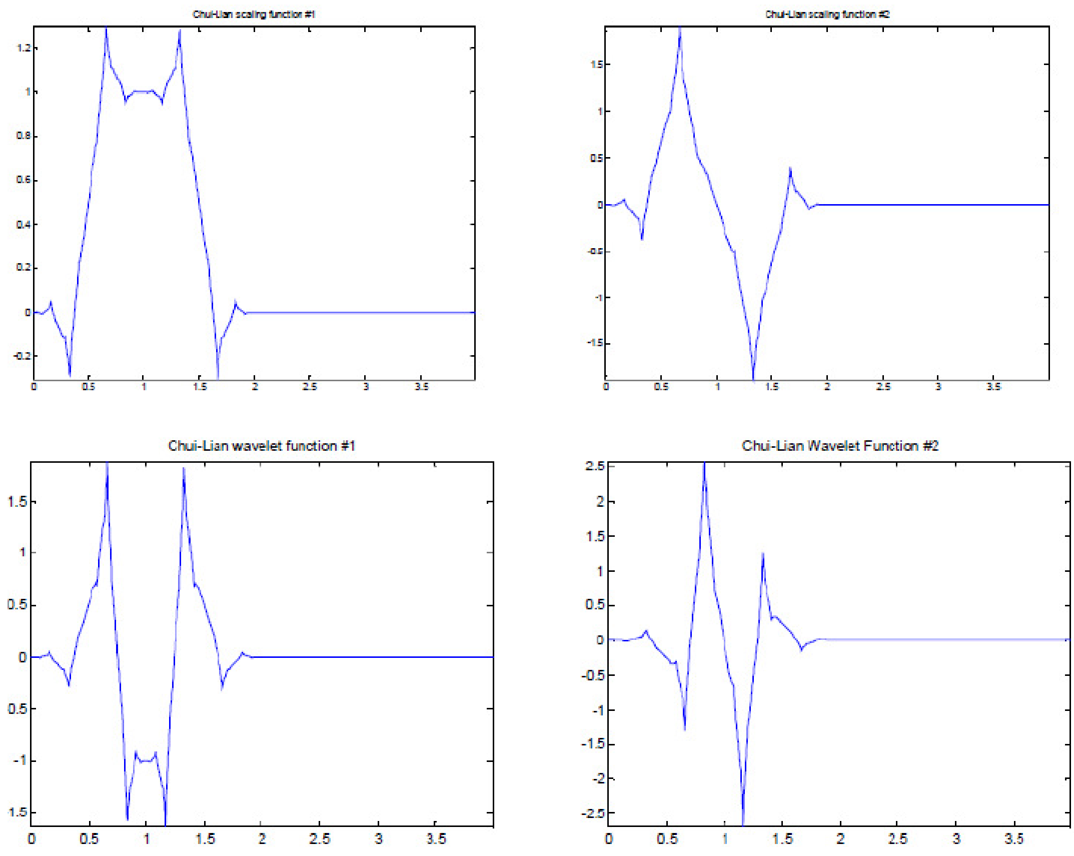



Fig.3.4 CL scaling and wavelet function, graphical representation

### 3.5. Medical Image Fusion with MultiWavelet Transform: -

Now-a-days wide research is being developed in medical image fusion using MutliWavelet Transform. CT and MRI image Fusion, PET and CT image Fusion has been performed using this technique. Two different modality images are considered. After passing through prefilter for vectorization, are transmiited from filter bank for decomposition. 16 subbands with multiplicity 2 are obtained. Corresponding subbands are fused using any of the fusion technique such as average method, maximum-minimum method, PCA based method, and feature based method. Feature based method is the process in which characteristics feature of an image are calculated using any feature extractor. These feature values are compared for both the image components. New fused component would retain that part of the subband having larger feature value. Features such as intensity, edges, corner, spatial frequency, visibility can be extracted using the proper technique. Using these techniques a new frequency subband is created that is used to develop a fused image via inverse MultiWavelet Transform.

# Chapter 4

## Proposed Method

In the project, PET and MRI images considered for Medical Image fusion process. MRI is an intensity image of 256*256 size. PET image available is indexed image of 128*128 size. This image is first converted to the RGB image and resized to 256*256*3 image. Intensity component of this RGB image is now calculated taking average of the R component, G component and B component. Steps carried out to fuse two medical images: one MRI image and second PET image are listed as:

Step1. Image Registration: - In this process, two input images are aligned to each other. Here we are using intensity based image registration. In this function two intensity images, metric, optimizer and transformation type are specified. Metric outputs a scalar value of two images that describes their similarity. Optimizer defines the method to minimize and maximize the similarity metric. Transformation type defines the method for the alignment process of misaligned image with the reference image. In the project, MRI image is considered as reference image and PET is aligned with it.

Step2. Decompose the MRI image and PET registered intensity image with 2D GHM Multiwavelet Transform.

Step 3: - Extract all the frequency components of both the images. Detect the edge feature for the subbands obtained using Canny edge detector. Canny edge detector is a complex but accurate detector and it is based on these 3 following objectives:

1. Low Error Rate
2. Edge points should be well localized
3. Single Edge Point Response

Steps to extract edges using canny edge detector are as follows

a. Smooth the input image with a Gaussian filter

b. Compute the gradient magnitude and angle images

c. Apply non-maxima suppression to the gradient magnitude image

d. Use double thresholding and connectivity analysis to detect and link edges

Fused component $CS_f$ ($LL_f$, $LH_f$, $HL_f$, $HH_f$) is obtained by assigning it the value with maximum edge of the components as

$$CS_f = CS_1, \quad \text{if } E_{CS(1)} \geq E_{CS(2)}$$

$$CS_f = CS_2, \quad \text{otherwise}$$

Step5. Obtained fused components are grouped as

$$X = [LL_f, LH_f; HL_f, HH_f]$$

And the resultant fused image is obtained by taking inverse MultiWavelet transform of X using IGHM function.

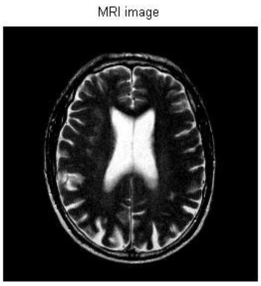
$$Y = IGHM(X)$$

Y represents the medical image fusion of MRI and PET image.

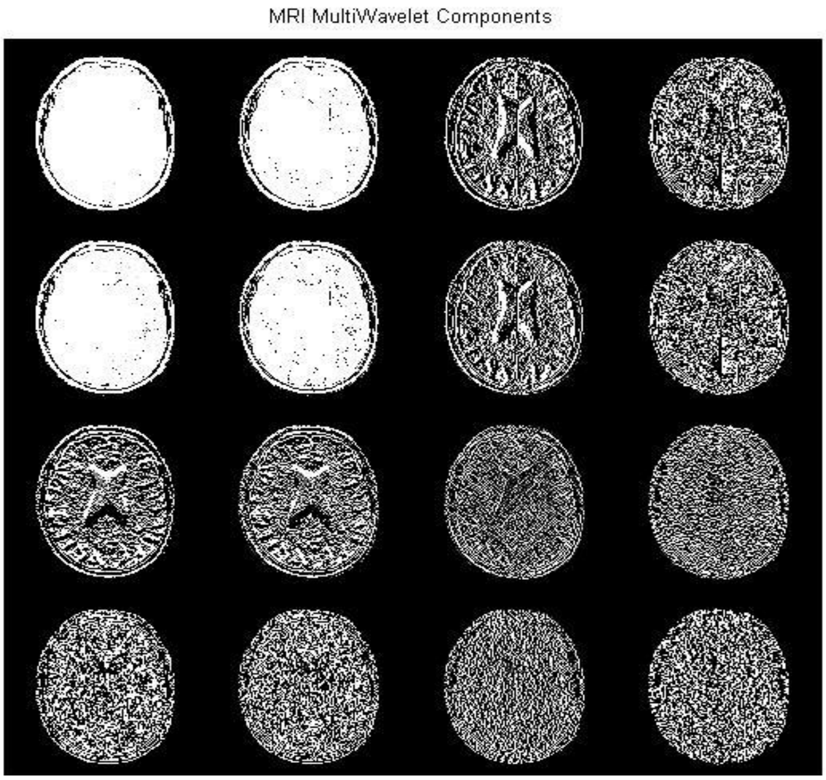
# Chapter 5

## Experimental Results

Seven different data sets for different diseases have been used for the experiment. Images are available in png and gif format. Here MRI image is the image of brain suffering from Alzheimer disease. Its decomposition is represented along with the image.

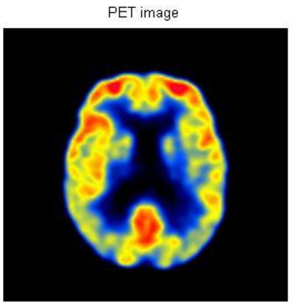



**(a)**

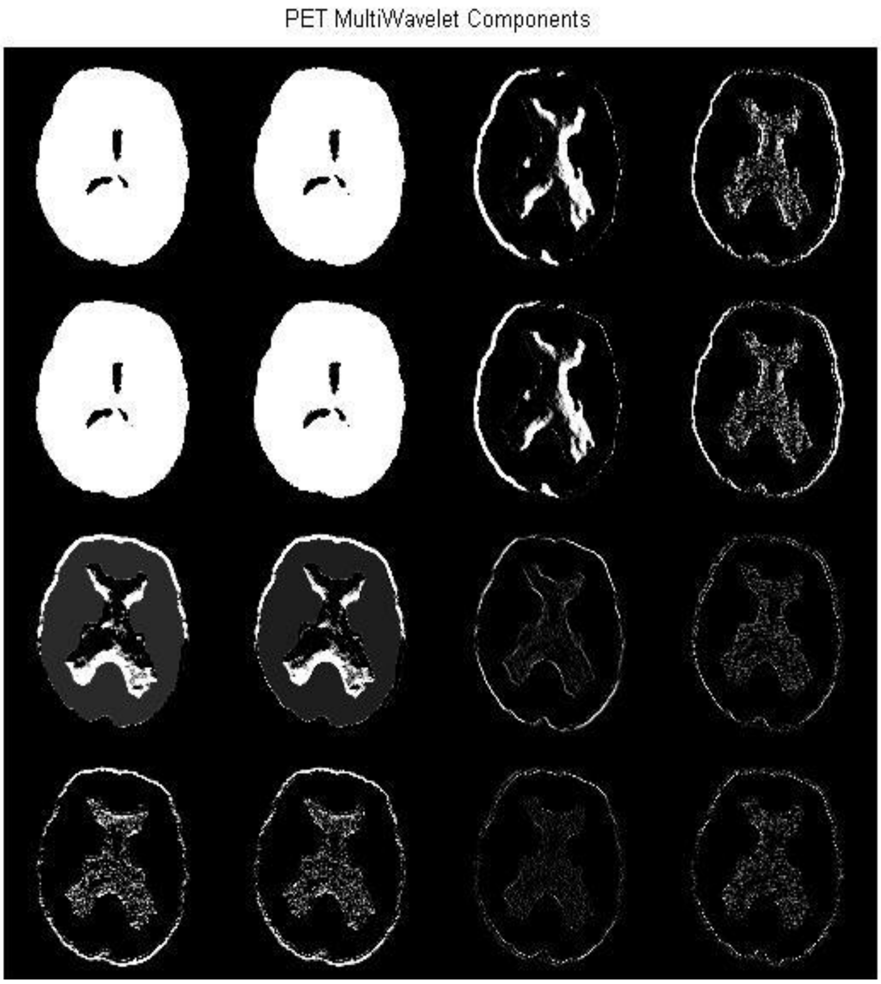



**(b)**

Fig.5.1. (a) MRI input image (b) MultiWavelet components of MRI image using GHM MultiWavelet decomposition




**(a)**




**(b)**

Fig.5.2. (a) PET input image (b) MultiWavelet components of PET decomposed using GHM MultiWavelet

Experiment 1

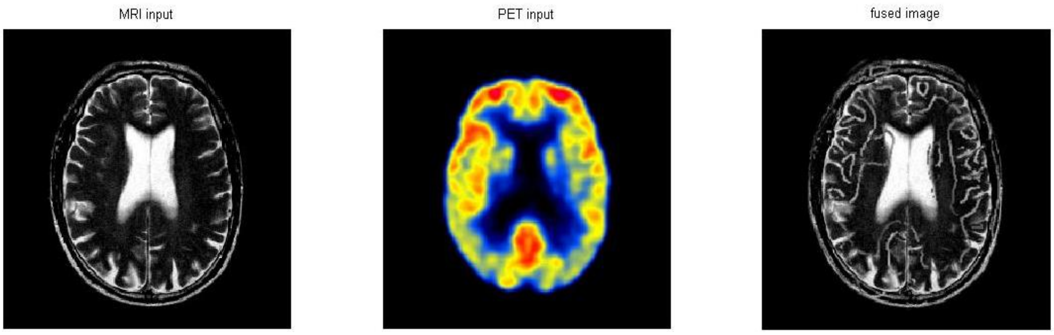



Fig.5.3. Data set 1: Image fusion of MRI and PET images using MultiWavelet for Alzheimer diseased person (a) original MRI image (b) original PET image (c) fused image

Experiment 2

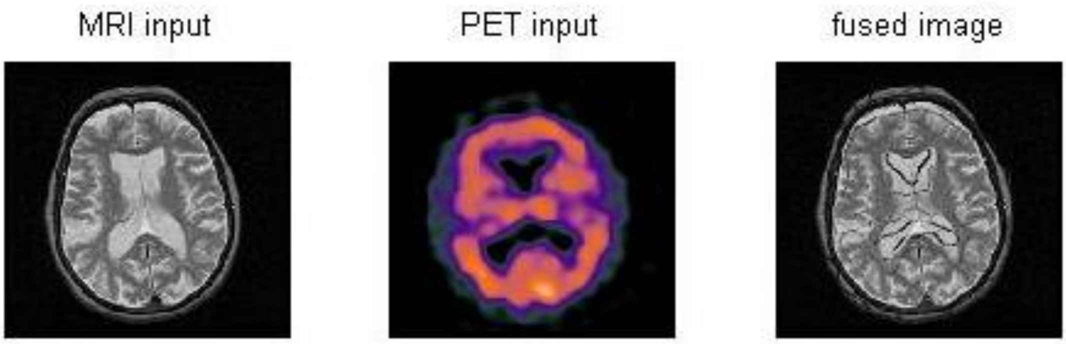



Fig.5.4. Data set 2: Image fusion of MRI and PET images using MultiWavelet for Huntigton's diseased person (a) original MRI image (b) original PET image (c) fused image

Experiment 3

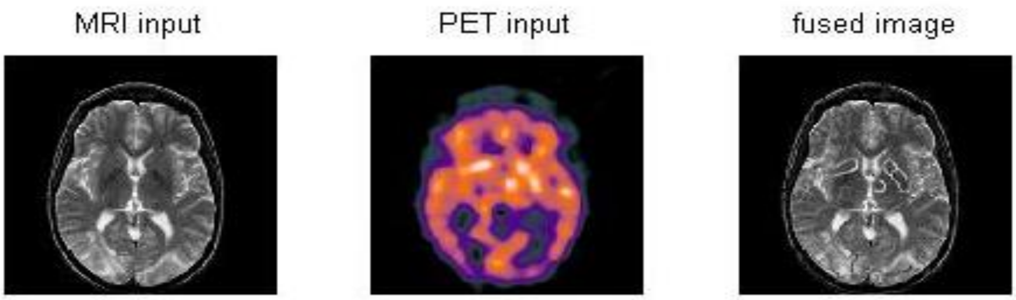



Fig.5.5. Data set 3: Image fusion of MRI and PET images using MultiWavelet for Hypertensive encephalopathy diseased person (a) original MRI image (b) original PET image (c) fused image

Experiment 4

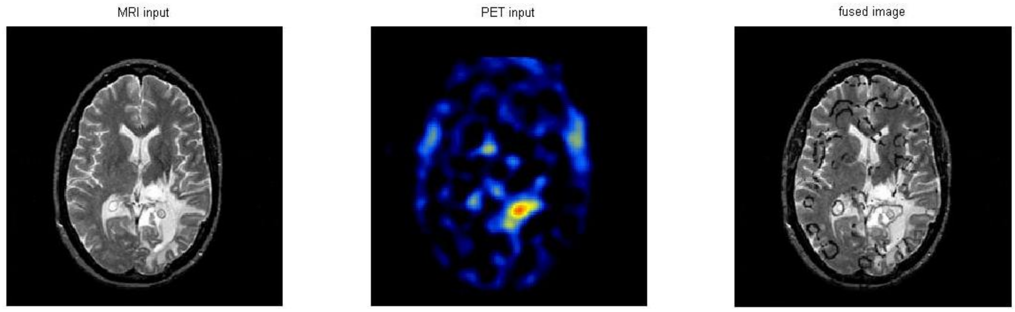



Fig.5.6. Data set 4: Image fusion of MRI and PET images using MultiWavelet for Brain Tumor's diseased person (a) original MRI image (b) original PET image (c) fused image

Experiment 5

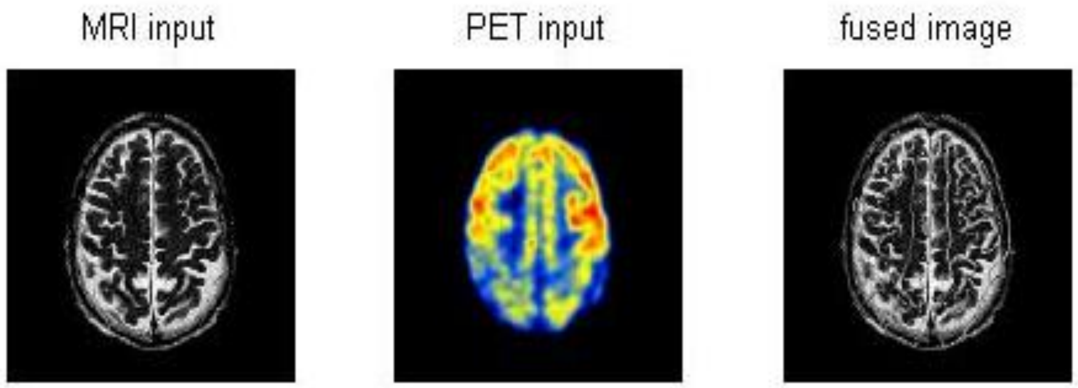



Fig.5.7. Data set 5: Image fusion of MRI and PET images using MultiWavelet for Normal Brain's diseased person (a) original MRI image (b) original PET image (c) fused image

Experiment 6

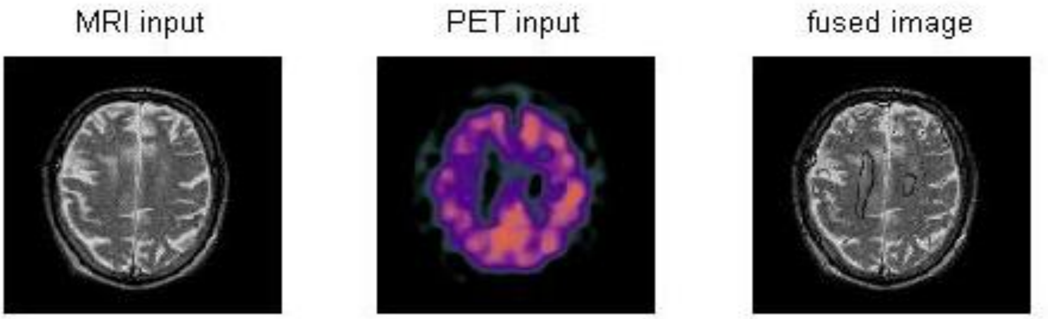



Fig.5.8. Data set 6: Image fusion of MRI and PET images using MultiWavelet for Motor neuron's diseased person (a) original MRI image (b) original PET image (c) fused image

Experiment 7

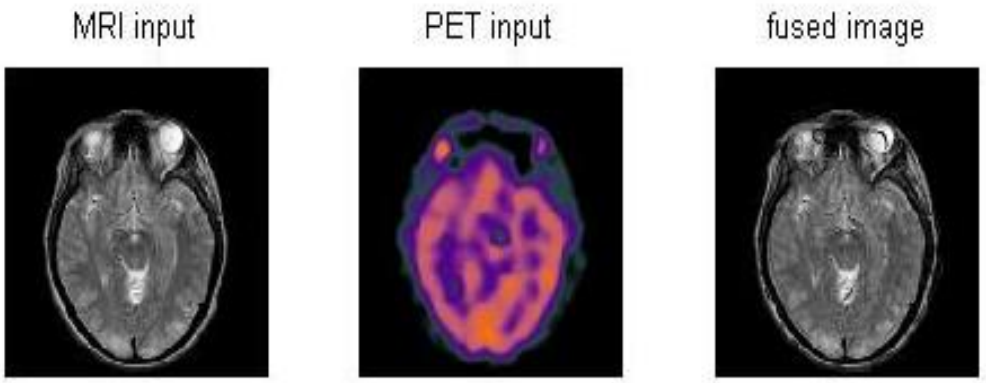



Fig.5.9. Data set 7: Image fusion of MRI and PET images using MultiWavelet for Hypertensive's diseased person (a) original MRI image (b) original PET image (c) fused image

## Result Analysis

Results obtained are analysed using entropy. Entropy is the information content of the image. The entropy of MRI image, PET image and Fused image of each data set is shown in the form of table given below

| | MRI Original image | PET Original image | Fusion using MultiWavelet |
|---|---|---|---|
| Data Set 1 | 3.4513 | 3.5682 | 4.2346 |
| Data Set 2 | 4.9114 | 3.7436 | 5.7830 |
| Data Set 3 | 3.4684 | 3.6017 | 4.3824 |
| Data Set 4 | 3.2052 | 2.3608 | 3.9624 |
| Data Set 5 | 3.3094 | 3.0756 | 4.1606 |
| Data set 6 | 3.1021 | 2.5942 | 3.6562 |
| Data set 7 | 3.4459 | 3.5477 | 4.3530 |

Fig.5.10. Data set 7: Table representing the entropy of MRI image, PET image and fused image of each data set

# Chapter 6

## Conclusion

From the above result we conclude that the image fusion using MultiWavelet provides better result. It captured the effected area from two images and represent it in a single image clearly specifying the disease in brain. It efficiently merge the two images and diagnose the brain disease.

Table contains the entropy value of the images. Here it justify that information content of the fused image is higher than each source image in each data set. It provides the anatomical information of MRI image along with the precise information of PET image in a single fused image using MultiWavelet Transform. It can be further improved by increasing the multiplicity, i.e. increasing the number of scaling and wavelet function as it will provide more fine details of the images.

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