OPTIMAL MEDICAL IMAGE FUSION WITH IMPROVED SPECTRAL EFFICIENCY

PROJECT REPORT

Submitted by

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DECLARATION

I undersigned hereby declare that the project report ("Optimal Medical Image Fusion with Improved Spectral Efficiency") , submitted for partial fulfillment of the requirements for the award of degree of Master of Computer Applications of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under supervision of Prof. Fousia M Shamsudeen. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

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CERTIFICATE

This is to certify that, this report entitled **OPTIMAL MEDICAL IMAGE FUSION WITH IMPROVED SPECTRAL EFFICIENCY** is a bonafide record of the submitted by **SURABHI S (TKM16MCA30)**, to the APJ Abdul Kalam Technological University in partial fulfillment of the requirements for the award of the Degree of Master of Computer Applications is a bonafide record of the project work carried out by her under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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SURABHI S

ABSTRACT

Image fusion is the process of combining two or more images by extracting the salient features from each images and creating a new one with extended information content. The created image will be a more informative one and it should posses all the features of the original images. The proposed system focuses on fusing MRI and PET image to obtain better and improved information based on optimal approximation and efficient detailed coefficient fusion. The given input (MRI) and reference (PET) image is first pre-processed to remove noisy contents and then undergoes a decimated discrete wavelet transform. We use Haar as decimated image transform. Then transformed coefficient undergo improved frequency base fusion (detailed coefficients undergo spectral fusion) and optimal weightage fusion (approximation coefficient undergo weightage fusion based on Flower Pollination Algorithm Optimization). Then an inverse Haar will be performed to obtain the fused result. The various result analysis shows the proposed method out performs all the traditional ones. The wavelet transform is an efficient image fusion method. In that we use discrete wavelet transform, which is more efficient because it captures both frequency as well as location information from an image.

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Chapter 1

INTRODUCTION

An image is a pictorial representation of visual perception. It is a two dimensional or three dimensional representation of an object with distributed amplitude of colorus. The applications of image fusion are include satellite image fusion, medical image fusion, remote sensing, computer vision, robotics.

The purpose of image fusion is to reduce the ambiguities and maximize the fusion information. Medical image fusion is to collect the information of multi-modality image together, to express information got from multi-modal images in one image at the same time to highlight their respective advantages, to carry out complimentary information and to provide comprehensive morphology and functional information which reflects physiological and pathological changes .Multi-source medical image fusion methods are mainly divided in to three categories: pixel- level based image fusion, feature-level based image fusion and decision-making based image fusion.

Image fusion is the gathering of all the information from multiple images to a single one, to make the image more informative and accurate than any single input image. Image fusion is not only to reduce noisy data but also to improve its efficiency and to make more understandable to human as well as machine prediction.

In this project we fuse medical images such as MRI and PET for getting a fused image. Thus the fused image get a high spectral and special efficiency which helps in disease prediction more easily.

1.1 PROBLEM DEFINITION

Image fusion involves extracting necessary information from a single or multiple images for different purposes. Recently there are different images, from that best one is opt. Different types of images need different types of fusion methedologies. Adaptive fusion is one of the best fusion method by redusing the noisy data and extraction information. Later analysing the fused images using certain factors such as RMSE, PSNR, MB and SD.

1.2 OBJECTIVE

The main aim of the project is to create a medical image fusion for the cancer or tumour prediction by fusing MRI and PET images.

Features are :-

- Decomposition of image using haar, DWT:- Discrete Wavelet Transform is one of the best way to extract the edge details of an image.
- Haar decimated transform: - Reduce the noisy data form input images.ie, it extact only certain needed values.
- High efficient fusion:- Two methods , one maximization fusion and a weighted fusion.
- Reconstruct without data loss:- Inverse Haar transform reconstruct the fused image.
- Optimised weight value is used :- For fusion optimised weight value is used.

Chapter 2

LITERATURE SURVEY

Medical image fusion is the process of registering and combining multiple images from single or multiple imaging modalities to improve the imaging quality and reduce randomness and redundancy in order to increase the clinical applicability of medical images for diagnosis and assessment of medical problems.

In [1] Bahareh Shalchian PhD et. al suggested that While information about anatomy is available in CT images, information about physiology and me- tabolism is available in PET images. To integrate both information, the two images are fused. Image fusion methods include simple methods like pixel averaging and sophisticated methods like wavelet transformation. An advantage of using wavelet transformation is that it preserves significant parts of each image. After creating lesions of 10, 8, 6 mm in a NURBS (non-uniform rational B-splines) based cardiac torso (NCAT) phantom, PET images were simulated using SimSET simulator. Attenuation maps of the activity phantom were used as CT images. Each of the PET and CT images was divided into an approximation image and three detailed images by the wavelet transform. The correspond- ing transformed images generated from the PET and CT images were fused in nine different ways to generate composite images, which were compared to the original images. The basis of comparison is the lesion-to-tissue contrast in the fused image in comparison to the lesion-to-tissue contrast in the original PET and CT images. Our results showed that except for one method, the lesion-to-tissue con- trast in the fused image was higher than that of the CT images. In the first six methods, the lesion-to- tissue contrast in the fused image was less than the contrast, in the PET image. In the other three methods, the contrast in the fused image was higher than in the PET image. This was true in cases of 10, 8, 6 mm lesions. In conclusion, show that the approximation image produced a better ul- the proposed system timate image and that the lesion-to-tissue contrast in the fused image was also better than that of the original PET and CT images. This is because the approximation image is comprised of fundamen- tal information of the signal (low frequency) that directly affects the image contrast.

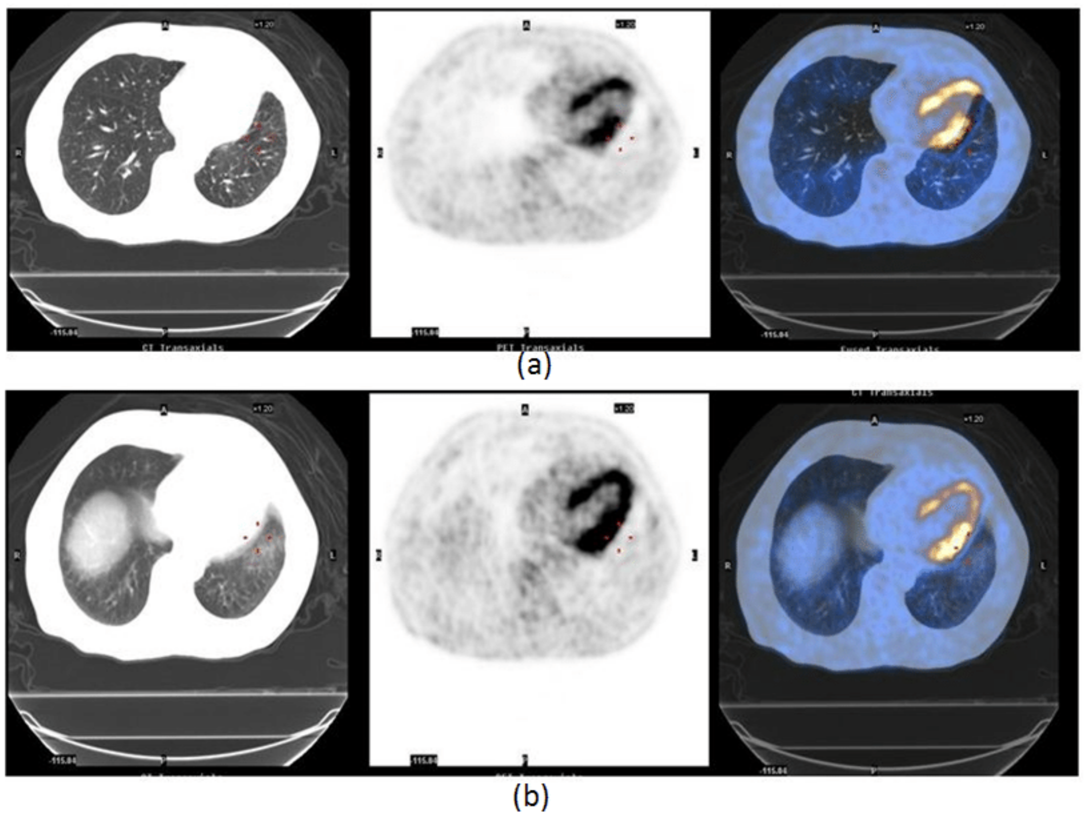

Figure 2.1: From left to right: CT image and simulated PET image of the phantom and the fused image

Suman Deb et.al studied that Advances in technology have brought about extensive research in the field of image fusion. Image fusion is one of the most researched challenges of Face Recognition. Face Recognition (FR) is the process by which the brain and mind understand, interpret and identify or verify human faces.. Image fusion is the combination of two or more source images which vary in resolution, instrument modality, or image capture technique into a single composite representation. Thus, the source images are complementary in many ways, with no one input image being an adequate data representation of the scene. Therefore, the goal of an image fusion algorithm is to integrate the redundant and complementary information obtained from the source images in order to form a new image which provides a better description of the scene for human or machine perception. In this paper the proposed system proposed a novel approach of pixel level image fusion using PCA that will remove the image blurredness in two images and reconstruct a new de-blurred fused image. The proposed approach is based on the calculation of Eigen faces with Principal Component Analysis (PCA). Principal Component Analysis (PCA) has been most widely used method for dimensionality reduction and feature extraction. [2]

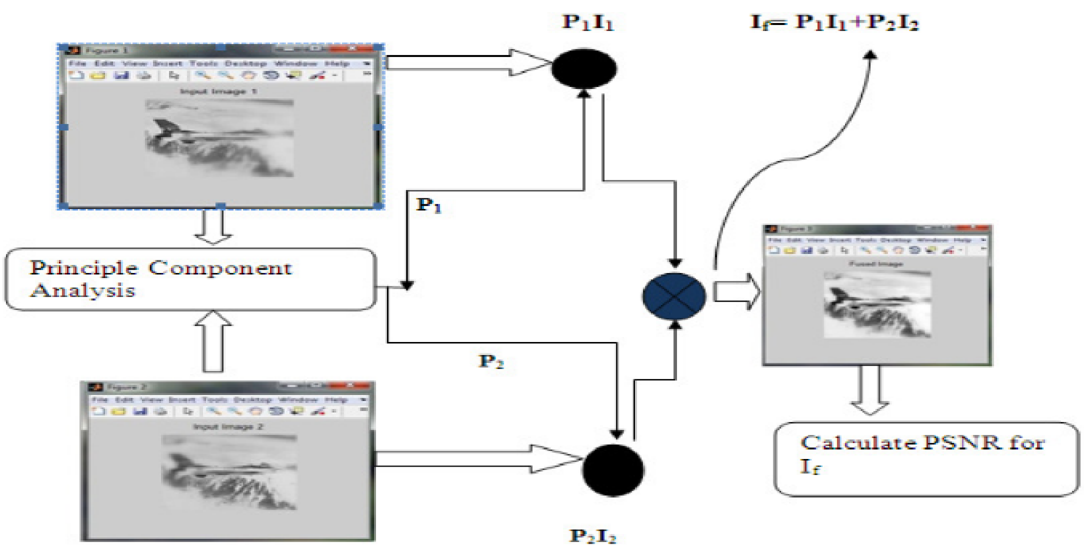

Figure 2.2: System design

Reham Gharbia et. al This paper proposes a multi-spectral (MS) and panchromatic (Pan) image fusion approach based on the flower pollination algorithm optimization (FPA). The FPA is used to get an optimal fused image. The image fusion quality depends on the choice of the weight of fusion rule. The proposed approach uses FPA to optimize the weights of a fusion rule to make a perfect image fusion process. FPA is a nature- Inspired algorithm, based on the characteristics of a flower pollination process. FPA averts trapping in local optimal solution. In this paper, the remote sensing image fusion based on flower pollination algorithm is compared to several states of the art image fusion approaches including Intensity-hue-saturation (IHS) image fusion; stationary wavelets transform image fusion based on the average weight fusion rule (SWT- AW) and the image fusion based on the particle swarm optimization (PSO). The experimental results used MODIS satellite series with spatial resolutions 250 m, 500 m, and 1 km, which are low spatial resolution and multispectral images; and Pan image of SPOT satellite is high spatial resolution 10 m to produce synthetic imagery at SPOT spatial resolutions and MODIS multispectral resolution at the same time. The experimental results prove that the proposed remote sensing image fusion approach can illustrate a better performance than the other approaches. The experimental results show that the approach offers upto 20% enhancement in Peak Signal to Noise Ratio (PSNR), 1% enhancement in Structural Similarity Index (SSIM), 1% and 0.5% enhancement in entropy information (EI) than best existing particle swarm optimization (PSO) approach. The results indicate that the proposed approach outperforms over existing approaches.[3]

In[4] Jingming Xia et. al The clinical assistant diagnosis has a high requirement for the visual effect of medical images. However, the low frequency sub band coefficients obtained by the NSCT decomposition are not sparse, which is not conducive to maintaining the details of the source image. To solve these problems, a medical image fusion algorithm combined with sparse representation and pulse coupling neural network is proposed. First, the source image is decomposed into low and high frequency sub band coefficients by NSCT transform. Secondly, the K singular value decomposition (K-SVD) method is used to train the low frequency sub band coefficients to get the over complete dictionary, and the orthogonal matching pursuit (OMP) algorithm is used to sparse the low frequency sub band coefficients to complete the fusion of the low frequency sub band sparse coefficients. Then, the pulse coupling neural network (PCNN) is excited by the spatial frequency of the high frequency sub band coefficients, and the fusion coefficients of the high frequency sub band coefficients are selected according to the number of ignition times. Finally, the fusion medical image is reconstructed by NSCT inverter. The experimental results and analysis show that the algorithm of gray and color image fusion is about 34% and 10% higher than the contrast algorithm in the edge information transfer factor QAB/F index, and the performance of the fusion result is better than the existing algorithm.

Umer Javed et.al An image fusion technique for magnetic resonance imaging (MRI) and positron emission tomography (PET) using local features and fuzzy logic is presented. The aim of proposed technique is to maximally combine useful information present in MRI and PET images. Image local features are extracted and combined with fuzzy logic to compute weights for each pixel.

Simulation results show that the proposed scheme produces significantly better results compared to state-of-art schemes.[5]

Behzad Kalafje Nobariyan et. al says that The fusion of multimodal brain imaging for a given clinical application is a very important performance. Generally, the PET (positron emission tomography) image indicates the brain function and it has a low spatial resolution, the MRI image shows the brain tissue anatomy and contains no functional information. In this paper, we propose a novel medical image fusion algorithm which enhances the spatial resolution of the functional images by combining them with a high-resolution anatomic image. In the event, after the registration process, perform YCbCr on the multispectral image and get luminance, blue-difference and red difference chromatic components, and then DWT (discrete wavelet transform) image fusion algorithm based on PCNN (pulse coupled neural networks) is applied to fuse the MRI image and the luminance component (Y). Ultimately, fused image is obtained by inverse YCbCr transform of the new luminance and the old blue-difference and red difference chromatic components back into RGB space. An important feature of the algorithm is to use PCNN because it has the global couple and pulse synchronization characteristics. It has been proven suitable for image processing and successfully employed in image fusion. Our approach is compared with YCbCr, DWT, Contourlet, Curvelet methods. Results show proposed method preserves more spectral features with less spatial distortion.[6]

B.S.Sathishkumar and Dr.G.Nagarajan The reconstruction of tomography imaging is often corrupted by means of a number of measurements, projection data, noise in measurement, computation time, resolution and prior knowledge. This paper presents a new approach called wavelet based image reconstruction for tomography by using different thersholding methods are investigated in the presence of choosing different wavelet filters. The quality of the reconstructed image is expressed in terms of mean square error (MSE) as compared to the original image and found as improved compared to other techniques.[7]

Do Kyung ShinYoung Shik Moon This paper proposes a novel method that combines the discrete wavelet transform (DWT) and example-based technique to reconstruct a high-resolution from a low-resolution image. Although previous interpolation- and example-based methods consider the reconstruction adaptive to edge directions, they still have a problem with aliasing and blurring effects around edges. In order to address these problems, in this paper, we utilize the frequency sub-bands of the DWT that has the feature of lossless compression. Our proposed method first extracts the frequency sub-bands (Low-Low, Low-High, High-Low, High-High) from an input low-resolution image by the DWT, and then the low-resolution image is inserted into the Low-Low sub-band. Since information in high-frequency sub-bands (Low-High, High-Low, and High-High) might be lost in the low-resolution image, they are reconstructed or estimated by using example-based method from image patch database. After that, we make a high-resolution image by performing the inverse DWT of reconstructed frequency sub-bands. In experimental results, we can show that the proposed method outperforms previous approaches in terms of edge enhancement, reduced aliasing effects, and reduced blurring effects.[8]

Jagalingam Pa,*, Arkal Vittal Hegde Image fusion is the process of combining high spatial resolution panchromatic (PAN) image and rich multispectral (MS) image into a single image. The fused single image obtained is known to be spatially and spectrally enhanced compared to the raw inputimages. In recent years, many image fusion techniques such as principal component analysis, intensity hue saturation, brovey transforms and multi-scale transforms, etc., have been proposed to fuse the PAN and MS images effectively. However, it is important to assess the quality of the fused image before using it for various applications of remote sensing. In order to evaluate the quality of the fused image, many researchers have proposed different quality metrics in terms of both qualitative and quantitative analyses. Qualitative analysis determines the performance of the fused image by visual comparison between the fused image and raw input images. On the other hand, quantitative analysis determines the performanceof the fused image by two variants such as with reference image and without reference image. When the reference image is available, the performanceof fused image is evaluated using the metrics such as root mean square error, mean bias, mutual information, etc. When the reference image is not available the performance of fused image is evaluated using the metrics such as standard deviation, entropy, etc. The paper reviews the various quality metrics available in the literature, for assessing the quality offused image.[9]

Particle swarm optimization (PSO) is one of those rare tools that's comically simple to code and implement while producing bizarrely good results. Developed in 1995 by Eberhart and Kennedy, PSO is a biologically inspired optimization routine designed to mimic birds flocking or fish schooling. I'll occasionally use PSO for CFD based aerodynamic shape optimization, but more often than not, it's for a machine learning project. PSO is not guaranteed to find the global minimum, but it does a solid job in challenging, high dimensional, non-convex, non-continuous environments. In this short introductory tutorial, I'll demonstrate PSO in its absolute simplest form. At a later date, I'll create another PSO tutorial featuring a more advanced implementation.[10]

In [11] Esteban Arroyo studied that Flexible and self-adaptive behaviours in automated quality control systems are features that may significantly enhance the robustness, efficiency and flexibility of the industrial production processes. However, most current approaches on automated quality control are based on rigid inspection methods and are not capable of accommodating to disturbances affecting the image acquisition quality, fact that hast direct consequences on the system's reliability and performance. In an effort to address the problem, this paper presents the development of a self-adaptive software system designed for the pre-processing (quality enhancement) of digital images captured in industrial production lines. The approach introduces the use of scene recognition as a key-feature to allow the execution of customized image pre-processing strategies, increase the system's flexibility and enable self-adapting conducts. Real images captured in a washing machines production line are presented to test and validate the system performance. Experimental results demonstrate significant image quality enhancements and a valuable reliability improvement of the automated quality control procedures

Xin-She Yang Flower pollination is an intriguing process in the natural world. Its evolutionary characteristics can be used to design new optimization algorithms. In this paper, wepropose a new algorithm, namely, flower pollination algorithm, inspired by the pollination process of flowers. We first use ten test functions to validate the new algorithm,and compare its performance with genetic algorithms and particle swarm optimization.Our simulation results show the flower algorithm is more efficient than both GA and PSO. We also use the flower algorithm to solve a nonlinear design benchmark, whichshows the convergence rate is almost exponential.[12]

Chapter 3

METHODOLOGY

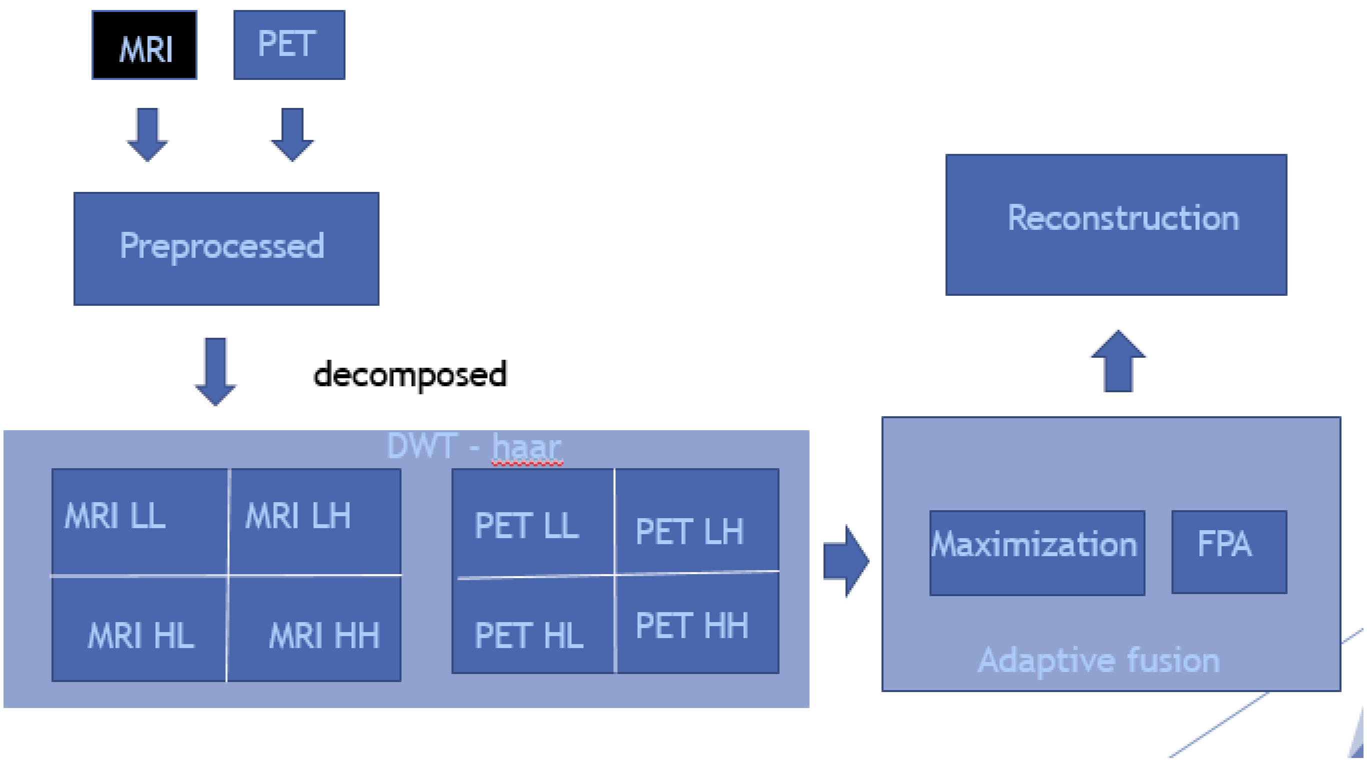

Figure 3.1: Work flow diagram.

Medical image fusion is the idea to improve the image content by fusing images taken from different imaging tools like Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) The objective of image fusion is to combine more useful information and remove redundant information from source registered images. In this survey paper, image fusion techniques are broadly classified into two categories;maximization fusion and weighted fusion. Various approaches in each category are discussed in detail. Comparative analysis is done based on the limitations and advantages of each method and quantitative analysis is conducted using Standard deviation and PSNR value.

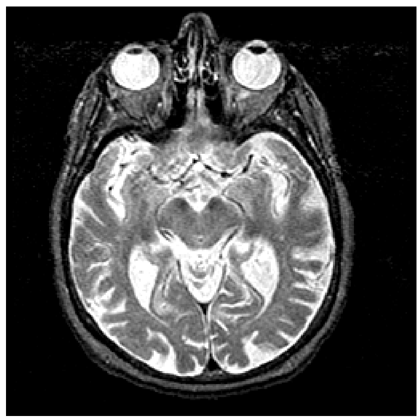

Figure 3.2: MRI image

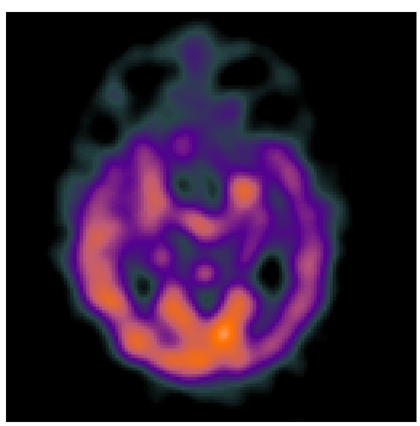

Figure 3.3: PEt image

3.1 Key Terms

- Pre-processing :- Pre-processing of images is to standardize both input and reference images to same pixel ratio.
- Decomposition :- Haar Decimated Discrete Wavelet Transform , which only extracts necessary edge values.
- Haar wavelet :- the Haar wavelet is a sequence of rescaled ”square-shaped” functions which together form a wavelet family or basis. Which has a peculiarities to remove noisy unwanted signals.
- Fusion :- weighted fusion and maximization fusion.
- Weight optimization :- Based on Flower pollination optimization algorithm
- Reconstruction of image :- Reconstruction is based on inverse haar transform.

The existing system is for fusing medical images ie, MRI as input and PET as reference image. So the fused image must have the spacial quality of MRI image and spectral Quality of reference image or PET image. The final output must be more similar to the reference image without any data loss other than noise.

The medical image fusion is an evolving research area with new inventions and theories. Here I have used DWT as transformation method so, the output of DWT is certain coefficients. Those coefficients matrices are of 4 types ie, an approximation matrix and 3 detailed image matrix coefficients.

These detailed image coefficients are fused based on spectral efficiency. If the spectral efficiency of MRI is greater compared to PET then fused image will be MRI. So Maximization algorithm is used here for fusion.

In case of approximation image, the fusion is weighted fusion. So the weight value is the optimum value taken through flower pollination algorithm optimization. Using those weight value we fuse the approximation image of MRI to PET.

Later we reconstruct those fused images into single one using inverse haar transform.

3.2 PREPROCESSING

The first phase

- It is the lowest level of abstraction and it is the first stage of noise reduction.
- The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing.
- Four categories of image pre-processing methods according to the size of the pixel neighborhood that is used for the calculation of a new pixel brightness:
  ⋆ pixel brightness transformations,
  ⋆ geometric transformations,
  ⋆ pre-processing methods that use a local neighborhood of the processed pixel, and
  ⋆ image restoration that requires knowledge about the entire image.
  Other classifications of image pre-processing methods exist.
- In this phase the input images undergo standardization by normalizing pixels of both input and reference images.

  Pixel Brightness Transformations
- Brightness transformations modify pixel brightness - the transformation depends on the properties of a pixel itself.

  ⋆ Brightness corrections
  ⋆ Gray scale transformations.
- The Gray scale transformations - It do not depend on the position of the pixel in the image.The aim - image with equally distributed brightness levels over the whole brightness scale.
- The Gray scale image is the Mono chromatic image with single light channel.
- Here the proposed system to convert the Gray coloured MRI image to Gray scale image. Because the initial gray colour may be the combination of RGB colours, so it is an image with

3 channels. Red channel , green channel and blue channel. The image with three channels cannot be directly fused or further processed. So we convert the RGB image into Gray scale image.

Figure 3.4: Sample Gray scale image

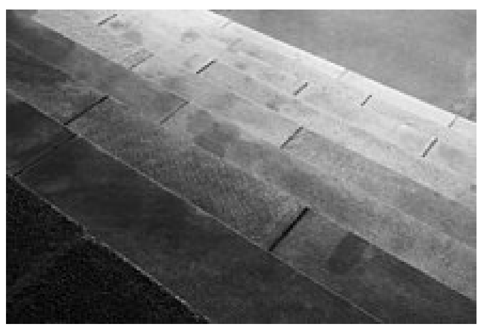

Figure 3.5: A sample image of colour image converted to gray scale

3.3 DECOMPOSITION

It is the second phase. Here we decompose the images with Haar -Decimated, Discrete Wavelet Transform.

- Transform The word ”transform” is something related to change.

3.3.1 WAVELET TRANSFORM

- A wavelet is a waveform of effectively limited duration that has an average value of zero. Comparing wavelets with sine waves, which are the basis of Fourier analysis. Sinusoids do not have limited duration they extend from minus to plus infinity and whereas sinusoids are smooth and predictable. Wavelets tend to be irregular and asymmetric.

Fig 3.1; Sine Wave

Fig 3.2: Wavelet (db10)

- Wavelets are a function with infinite length and which posses oscillatory in nature. Its applications are in signal processing such as image reconstructiob and noise reduction

$$\psi_{a,b} = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a})$$

  is the mathematical representation of wavelet and a, b are scaling and shifting parameters.

- A wavelet transform is transformation in wavelet , only in its time constrain not in its shape or feature.

- It is a mathematical function.- A function $\psi \in L^2(\mathbb{R})$ is called an orthonormal wavelet if it can be used to define a Hilbert basis, that is a complete orthonormal system, for the Hilbert space $L^2(\mathbb{R})$ of square integrable functions

3.3.2 PRINCIPLE

- The fundamental idea of wavelet transforms is that the transformation should allow only changes in time extension, but not shape. This is affected by choosing suitable basis functions that allow for this. Changes in the time extension are expected to conform to the

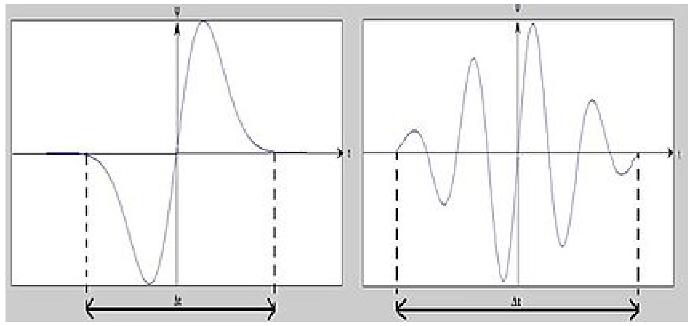

Figure 3.6: Wavelet Transform in time constrain

corresponding analysis frequency of the basis function. Based on the uncertainty principle of signal processing,

$$\Delta t \Delta \omega \gg \frac{1}{2}$$

where t represents time and ω angular frequency ($\omega = 2\pi f$, where f is temporal frequency).

- Wavelet transforms are divided into 3 classes: Discrete wavelet transforms (DWT), Continuous wavelet transforms (CWT) and multi resolution based wavelet transform.

3.3.3 DISCRETE WAVELET TRANSFORM (DWT)

- In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information (location in time).

- DWT works on two functions, namely scaling function and wavelet functions [13]. The analysis of signal at different scales is done by using the filters of different cut off frequencies. This decomposes the signal into different frequency bands, which are passed through the series of filters to analyse the high frequencies and low frequencies.

- The output of decomposition is 4 types of images. ie, an approximation image and three detailed image .

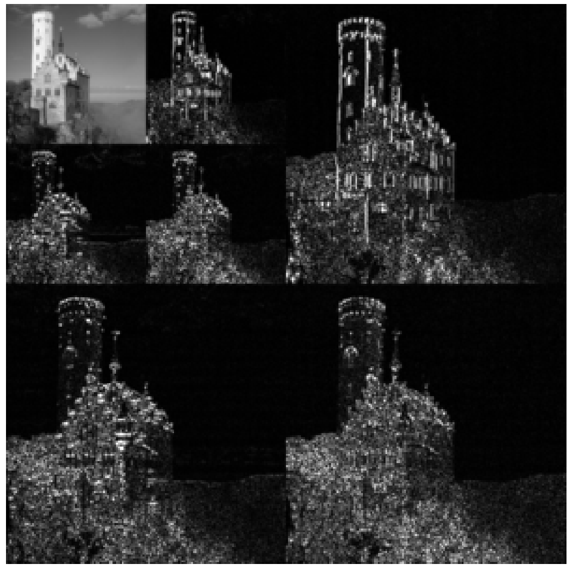

Figure 3.7: Example of decomposed image

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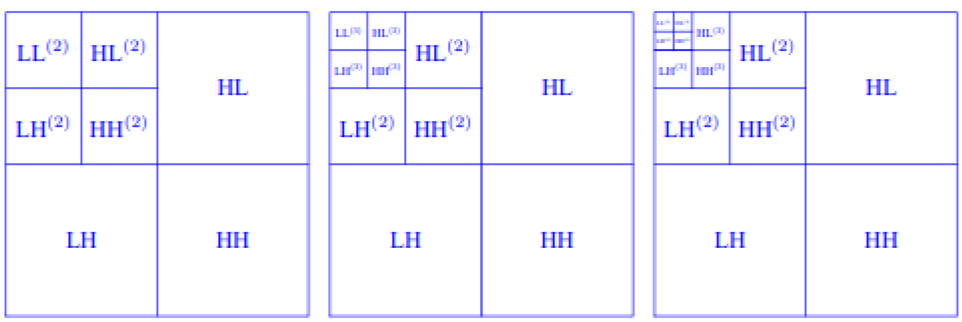

(a) two levels of 2D-DWT (b) three levels of 2D-DWT (c) four levels of 2D-DWT

Figure 3.8: multiresolution scheme after several levels of wavelet transform

3.3.4 HAAR WAVELETS

- The first DWT was invented by Hungarian mathematician Alfréd Haar. For an input represented by a list of 2^n numbers, the Haar wavelet transform may be considered to pair up

$$\mathbf{H}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \mathbf{H}_4 = \frac{1}{2} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & -1 & -1 \\ \sqrt{2} & -\sqrt{2} & 0 & 0 \\ 0 & 0 & \sqrt{2} & -\sqrt{2} \end{bmatrix}$$

Figure 3.9: $2X2$ and $4X4$ haar matrices

input values, storing the difference and passing the sum. This process is repeated recursively, pairing up the sums to prove the next scale, which leads to $2^n - 1$ differences and a final sum.

- Here first of all a haar transform is created of size $4X4$ and it is applied on input image to decompose the image.

  $$(image \circledast haar^T)^T \circledast haar^T$$

  where ”haar” is a matrix

- The Haar wavelet transform may be considered to simply pair up input values, storing the difference and passing the sum. This process is repeated recursively, pairing up the sums to provide the next scale, finally resulting in differences and one final sum.

- The Haar Wavelet Transformation is a simple form of compression which involves averaging and differencing terms, storing detail coefficients, eliminating data, and reconstructing the matrix such that the resulting matrix is similar to the initial matrix.

- A Haar wavelet is the simplest type of wavelet. In discrete form, Haar wavelets are related to a mathematical operation called the Haar transform. The Haar transform serves as a prototype for all other wavelet transforms.

- Like all wavelet transforms, the Haar transform decomposes a discrete signal into two sub-signals of half its length. One sub-signal is a running average or trend; the other subsignal is a running difference or fluctuation.

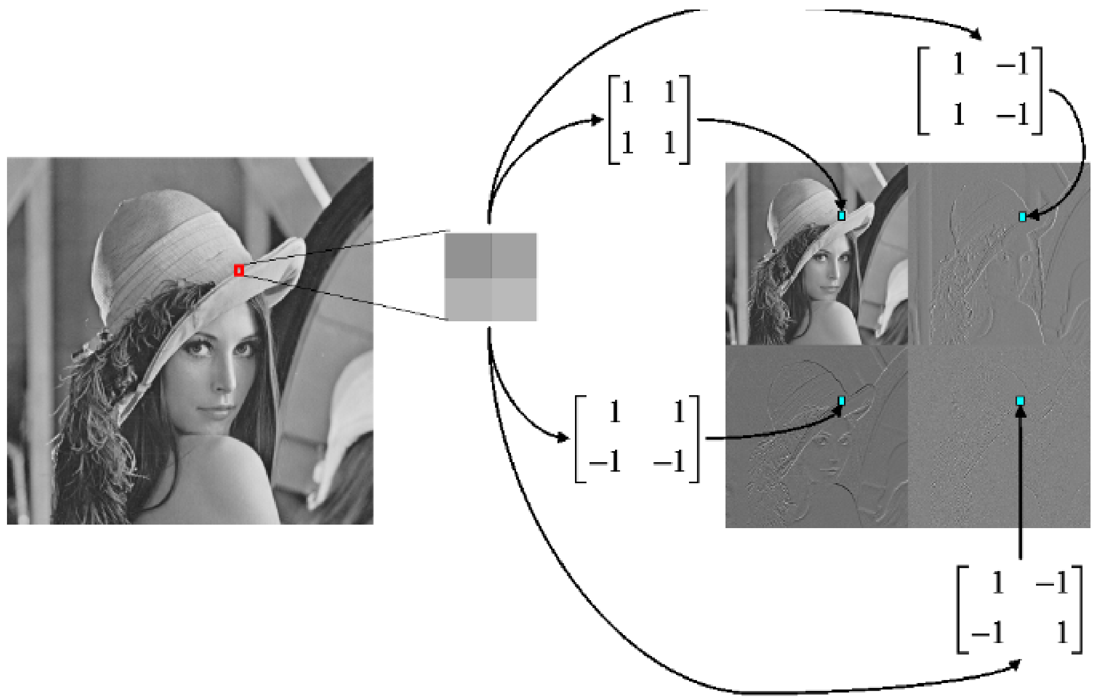

Figure 3.10: Haar decomposing images.

3.4 IMAGE FUSION

The output of decomposition is diffrent types ofg images or matrices. ie, one approximation matrix /image and remaining detailed images. these two images undergo diffrent types of fusion.

3.4.1 DETAILED IMAGE FUSION

The detailed images under go **spectral fusion** .

- First we divide each image into a block of sixe $15X15$
- On each block find row wise and column wise diffrence and calculate the **spectral frequency**.
- spectral frequency(SF) - is the intensity difference of an image.

$$SF = \sqrt{(rowdiffrence)^2 - (columndiffrence)^2}$$

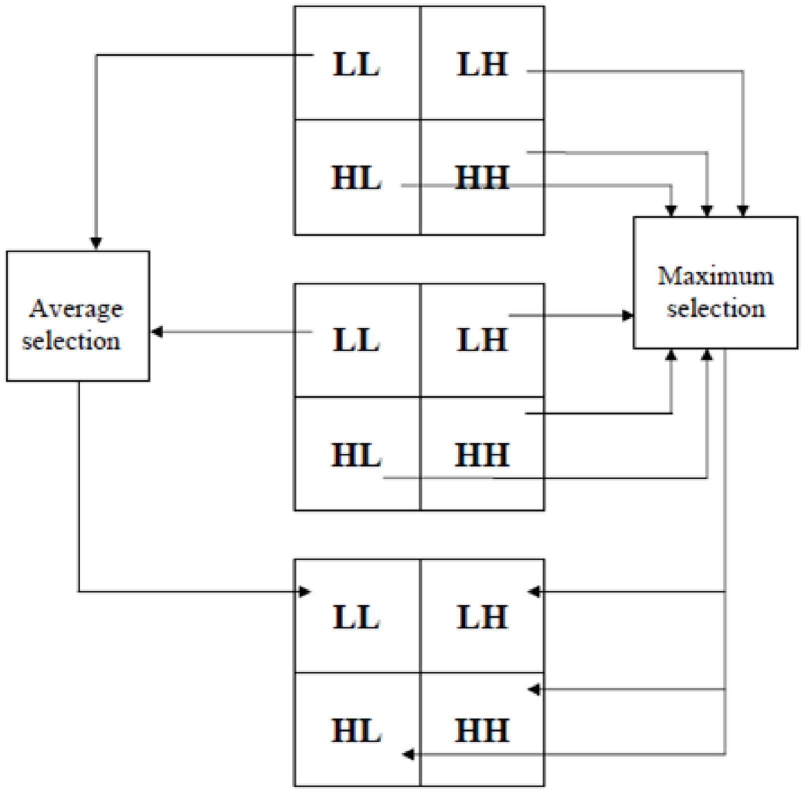

Figure 3.11: Detailed image fusion using maximization of sprectral efficiency.

PSEUDOCODE

Compare SF of PET with SF of MRI on each pixel.

if SF of MRI $\geq$ SF of PET

fused image = MRI

else if SF of PET $\geq$ SF of MRI

fused image = PET

else

fused image = (MRI + PET)/2

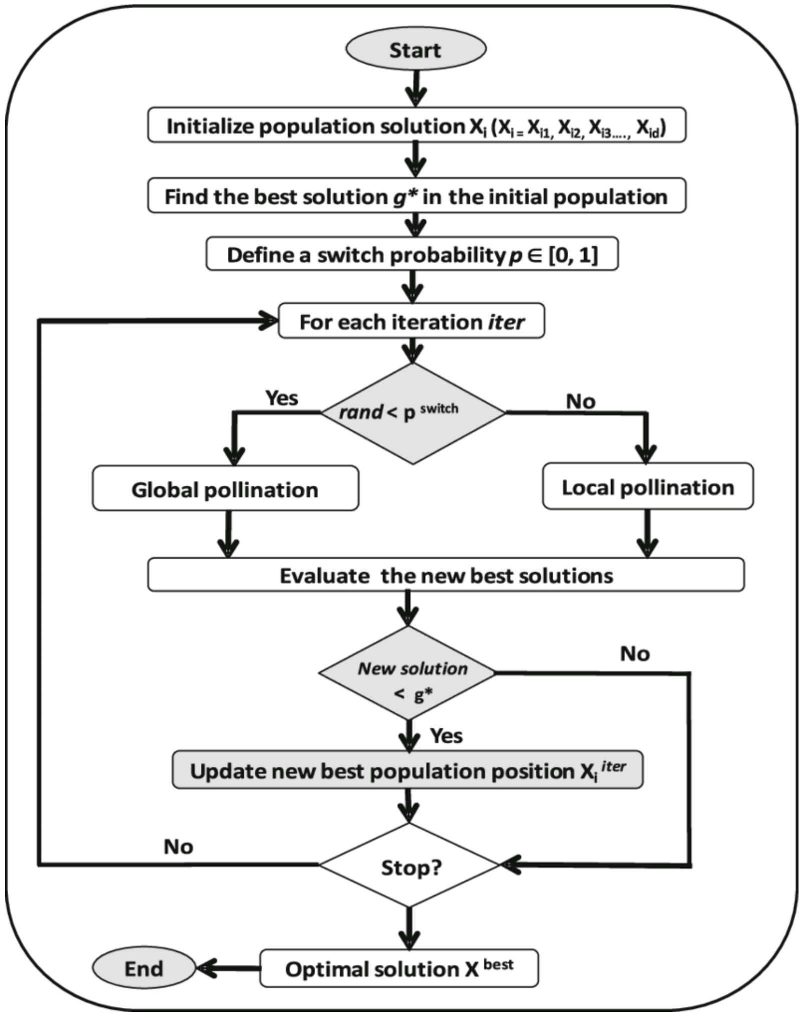

Figure 3.12: Flower pollination Algorithm optimization flow chart.

3.4.2 APPROXIMATION IMAGE FUSION

The approximation image is fused based on weighted fusion. The weight is the optimum value taken with Flower Pollination Optimization Algorithm.

FLOWER POLLINATION ALGORITHM (FPA)

- FPA is an intriguing process in the natural world. Its evolutionary characteristics can be used to design new optimization algorithms.Flower pollination algorithm, inspired by the pollination process of flowers. While comparing its performance with genetic algorithms and particle swarm optimization, it show the flower algorithm is more efficient than both GA and PSO.

- In FPA there are two types of solution Global and local solutions.
- For implimentation , first we create an initial population. Then find the optimal solution based on global and local solution.
- The optimal solution is the weight value which is used to fuse the approximation images
- Each weight values from the population is taken for image fusion and the diffrence between fused and PET image should be minimum, that weight value is called optimum weight.

$$C(x,y) = W * C_1(x,y) + (1-W) * C_2(x,y)$$

where W is the optimized weight value.

3.5 ALGORITHM

3.6 RECONSTRUCTION USING INVERSE HAAR

Image reconstruction is a mathematical process.Reconstructions that improve image quality.

- Two major categories of reconstruction methods exist, analytical reconstruction and iterative reconstruction (IR). Let's focus on the analytical reconstruction methods at first.
- When digital images are to be viewed or processed at multiple resolutions, the discrete Wavelet Transform (DWT) is the mathematical tool of choice. In addition to this, being an efficient, highly intuitive framework for the representation and storage of multi-resolution images, the DWT provides powerful insight into an image's spatial and frequency characteristics. Our project is a lossy compression since it uses a transform coding technique (by using DWT) and to perform the compression and reconstruction, MATLAB is used as a tool.

Table 3.1: Algorithm: Flower Pollination Algorithm

Objective min or max $f(x), x = (x_1, x_2, ..., x_d)$

Initialize a population of n flowers/pollen gametes with random solutions

Find the best solution g_* in the initial population

Define a switch probability $p \in [0,1]$

while*($t \ll MaxGeneration$)*

for i=$[1] : n(all n flowers in the population)$

if *rand* $\ll p$,

Draw a (d-dimensional) step vectorL which obeys a Levy distribution

Global pollination via $X_i^{t+1} = X_i^t + L(g_* - X_i^t)$

else

Draw $\in$ *from a uniform distribution in [0,1]*

Randomly choose j *and* k *among all the solutions*

Do local pollination via $X_i^{t+1} = X_i^t + \in (X_j^t - X_k^t)$

end if

Evaluate new solutions

If new solutions are better, update them in the population

end for

Find the current best solution g_*

end while

Table 3.2: Algorithm

Objective fused image, $f(x,y) = xy$
Input 2 *images* x,y $'x'$ *as input image and* $'y'$ *as reference image.*
Preprocess the image : Resize images x,y
Decompose each image (DWT): receive 4 decomposed coefficients $,LL,LH,HL,HH$
fuse LL of input and LL of reference : Approximation image Fusion using ***FPA Algorithm 3.1***
Find W, the optimal solution from Flower Pollination Algorithm
$C(x,y) = W * C_1(x,y) + (1-W) * C_2(x,y)$
fuse LH, HL,HH of input and reference image : Detailed image fusion

3.7 QUALITY ANALYSIS

Image fusion is the process of combining high spatial resolution MRI image and PET image into a single image. The fused single image obtained is known to be spatially and spectrally enhanced compared to the raw inputimages. In recent years, many image fusion techniques such as principal component analysis, intensity hue saturation, brovey transforms and multi-scale transforms, etc., have been proposed to fuse the MRI and PET images effectively. However, it is important to assess the quality of the fused image before using it for various applications of remote sensing. In order to evaluate the quality of the fused image, many researchers have proposed different quality metrics in terms of both qualitative and quantitative analyses.

Qualitative analysis determines the performance of the fused image by visual comparison between the fused image and raw input images. On the other hand, quantitative analysis determines the performanceof the fused image by two variants such as with reference image and without reference image. When the reference image is available, the performanceof fused image is evaluated using the metrics such as root mean square error, mean bias, mutual information, etc. When the reference image is not available the performance of fused image is evaluated using the metrics such as standard deviation, entropy, etc.

When the reference image is available, the following quality metrics such as *root mean square*

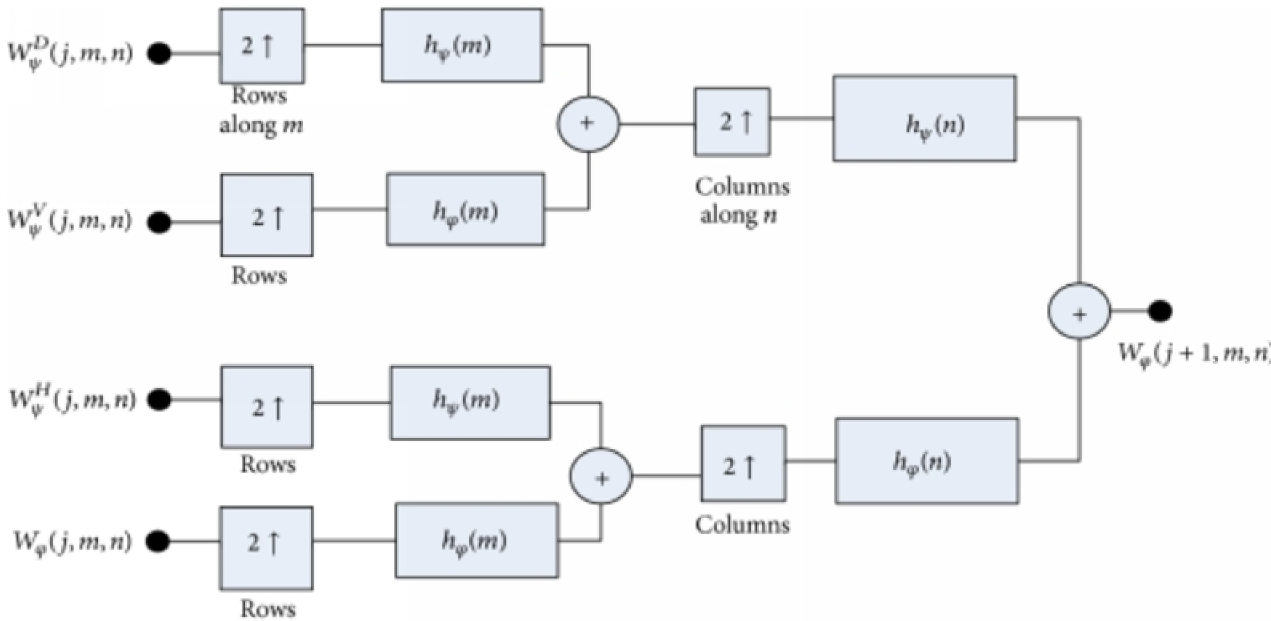

Figure 3.13: inverse DWT image reconstruction

error ***(RMSE)***, *mean bias* ***(MB)***,*standard deviation**(σ)***, *peak signal to noiseratio* ***(PSNR)*** etc.

3.7.1 ROOT MEAN SQUARE ERROR

The root-mean-square deviation (RMSD) or root-mean-square error (RMSE) (or sometimes root-mean-squared error) is a frequently used measure of the differences between values (sample or population values) predicted by a model or an estimator and the values observed. The RMSD represents the square root of the second sample moment of the differences between predicted values and observed values or the quadratic mean of these differences. These deviations are called residuals.

RMSD is always non-negative, and a value of 0 (almost never achieved in practice) would indicate a perfect fit to the data. In general, a lower RMSD is better than a higher one. RMSD is the square root of the average of squared errors.

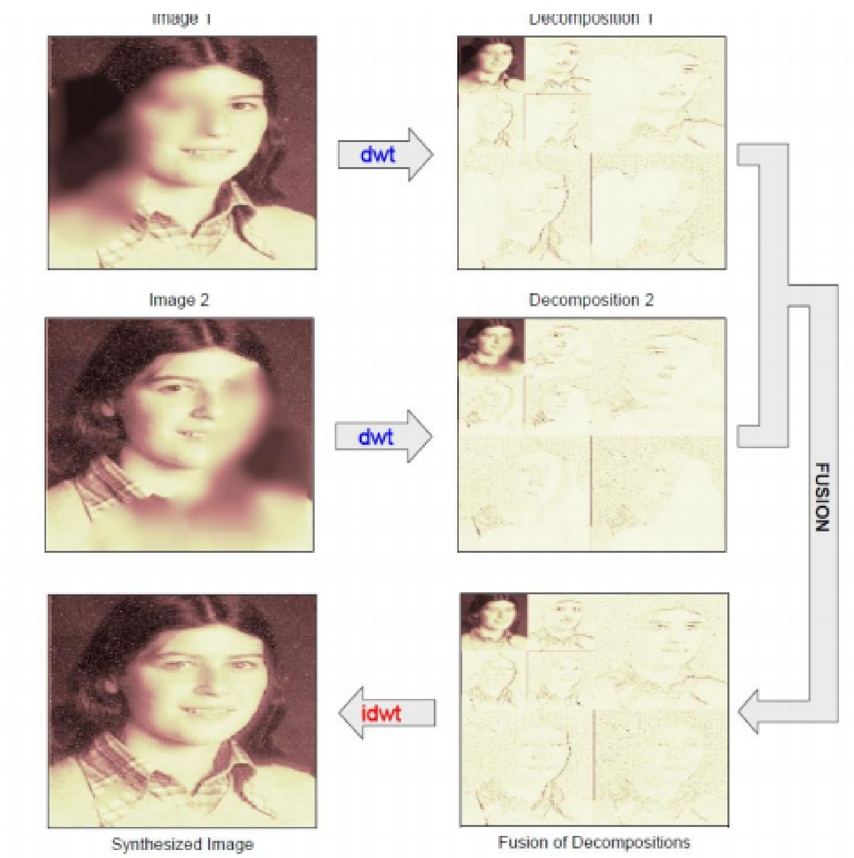

Figure 3.14: Image reconstruction using Haar.

3.7.2 MEAN BIAS

Mean Bias is the difference between the mean of the reference image and fused image. The ideal value is zero and indicates that the reference image and fused image are similar. Mean value refers to the grey level of pixels in an image

3.7.3 STANDARD DEVIATION

Standard deviation is used to measure the contrast in the fused image. When the value of Vis high, it indicates the fused image as high contrast.

3.7.4 PEAK SIGNAL NOISE RATIO

PSNR computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is used as a quality measurement between the original and a reconstructed image. The higher the PSNR, the better is the quality of the reconstructed image. To compute the PSNR, first the proposed system to compute the mean squared error (MSE) using the following equation:

Table 3.3: Perfomance evaluation table

Sl. No.	Quality matrics	Formula	value tends to BestFusion (Higher/Lower)	Reference
1	RMSE	$RMSE = \sqrt{\Sigma_i^M \Sigma_j^N [If(i,j) - Ii(i,j)]^2 (1/M*N)}$	Lower(close to zero)	Zoran, 200
2	ME	$MB = (Ref_i mg - Fused_i mg)/Ref_i mg$	Lower(equal to zero)	Yusuf et al.
3	SD	$\sigma = \sqrt{\Sigma_{i=0}^{l} (i - \bar{i})^2 h_{I_f}(i)}$	Higher	Wang and
4	PSNR	$PSNR = 20 \log_{10} L^2 / (\Sigma_M^N [If(m,n) - Ii(m,n)2/M*N])$	Higher	Naidu, 201

Chapter 4

RESULT And DISCUSSION

- In project the proposed system used best optimization algorithm for fusing medical images. ie, Flower Pollination Algorithm Optimization. It is proved in the base paper that this alorithm is best one compared to particle swarm optimization.
- Here we find the RMSE value, mean Bais value, PSNR value and Standard deviation value for calculating the efficiency of the image fusion.
- Below am displaying a single mode of PET and MRI image of brain and later fuse it with out lossing its features.

Input Images 1

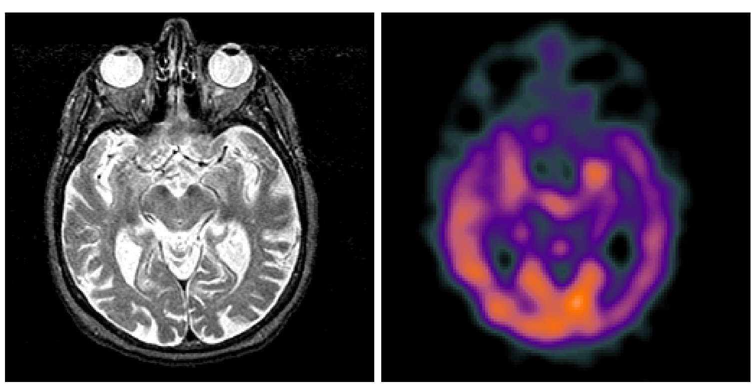

Figure 4.1: Input Image: MRI and Reference Image : PET.

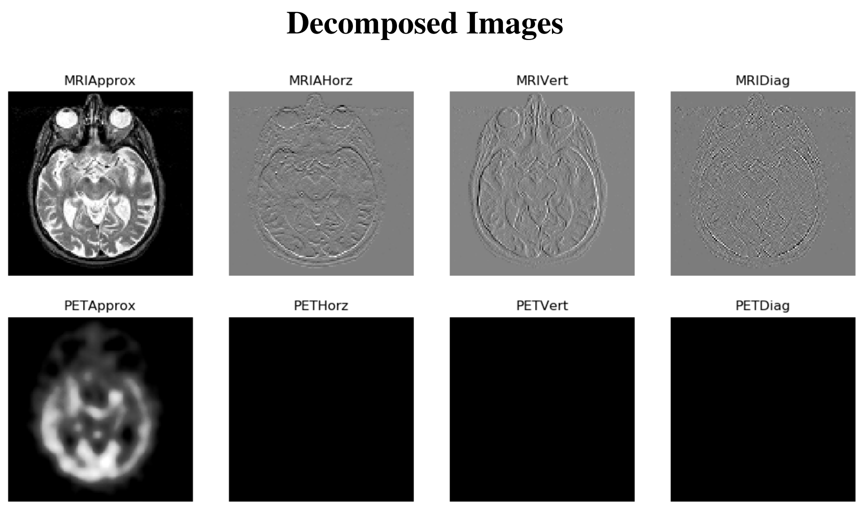

Figure 4.2: single level Decomposed MRI and PET images

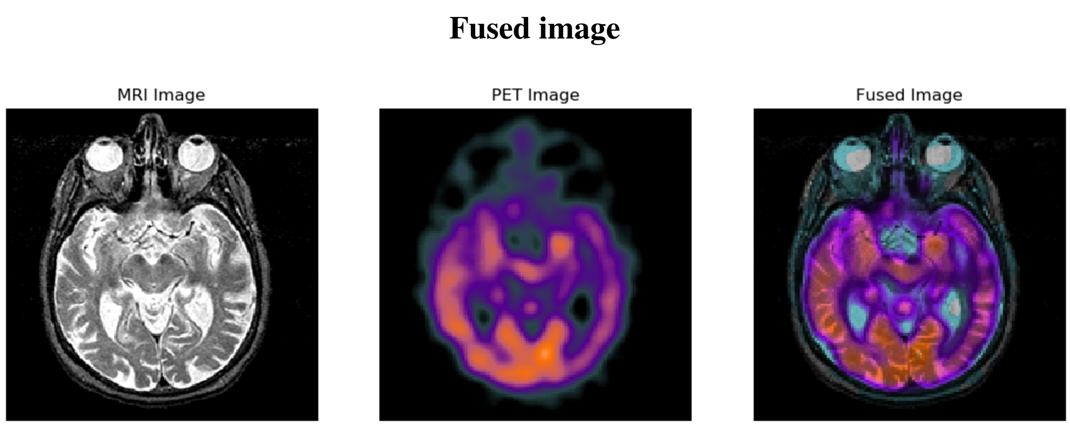

Figure 4.3: Input Images and Fused Image.

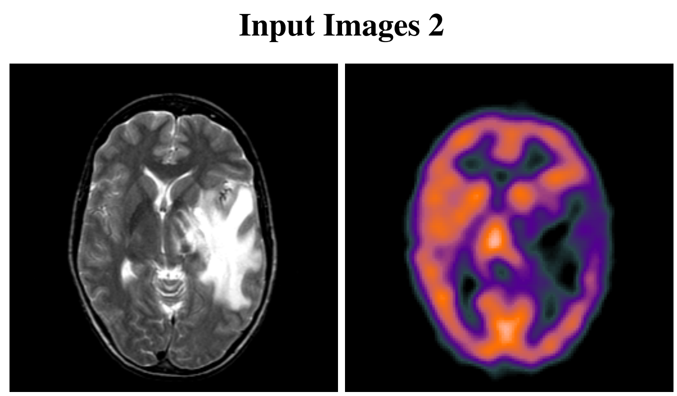

Figure 4.4: Input Image: MRI and Reference Image : PET.

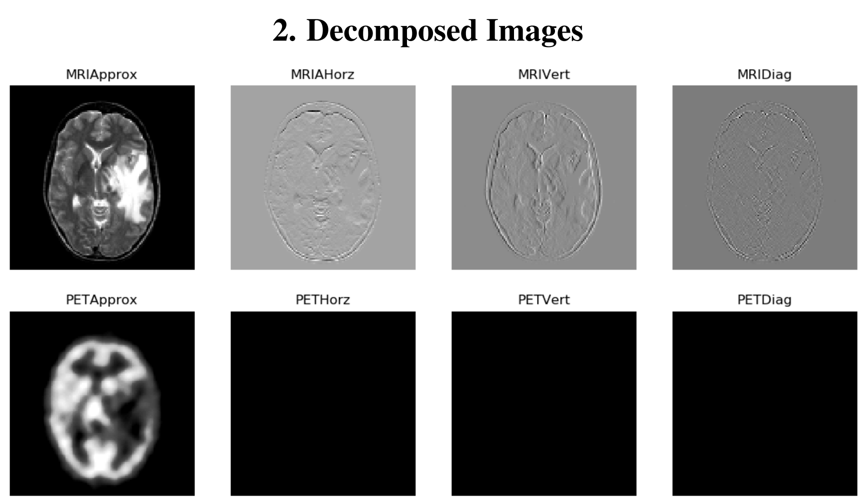

Figure 4.5: single level Decomposed MRI and PET images

2. Fused image

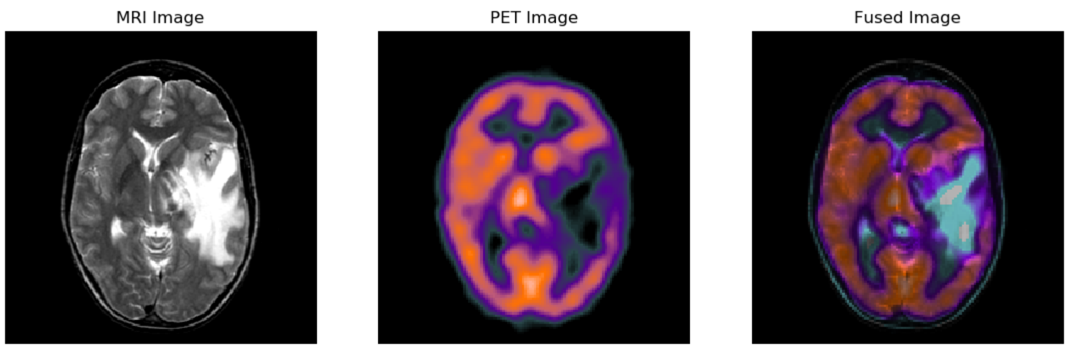

Figure 4.6: Input Images and Fused Image.

Input Images 3

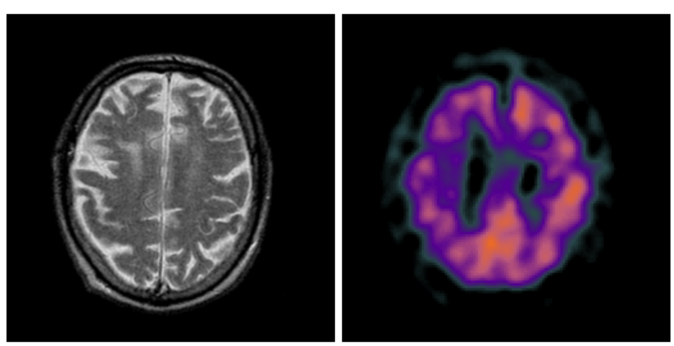

Figure 4.7: Input Image: MRI and Reference Image : PET.

3. Decomposed Images

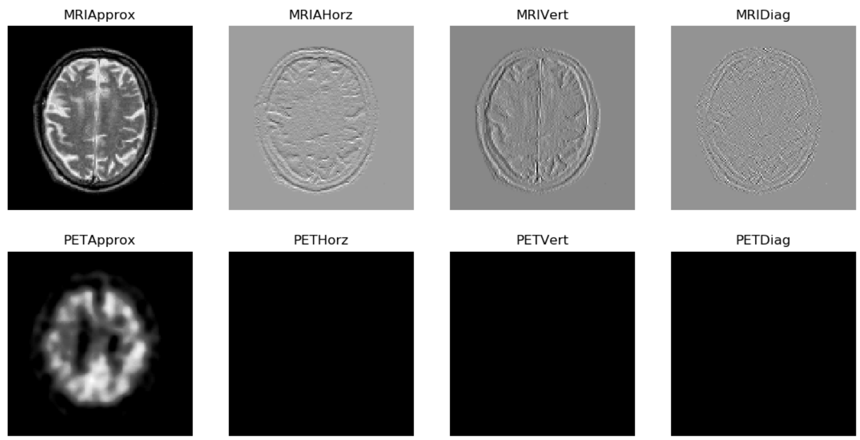

Figure 4.8: single level Decomposed MRI and PET images

3. Fused image

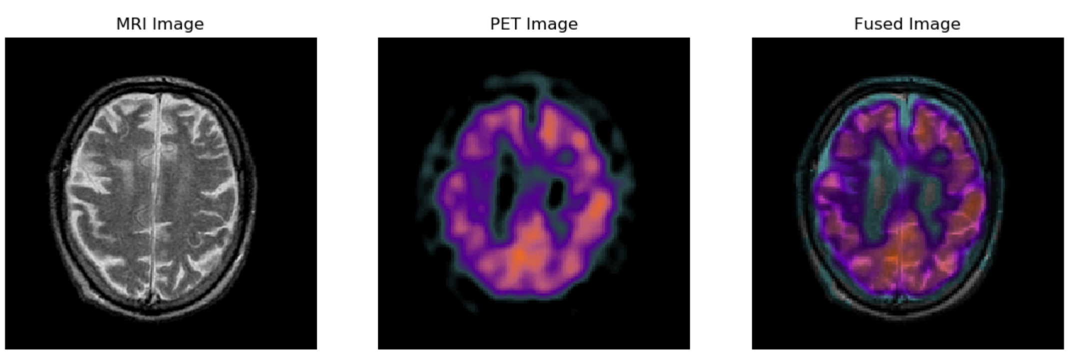

Figure 4.9: Input Images and Fused Image.

Input Images 4

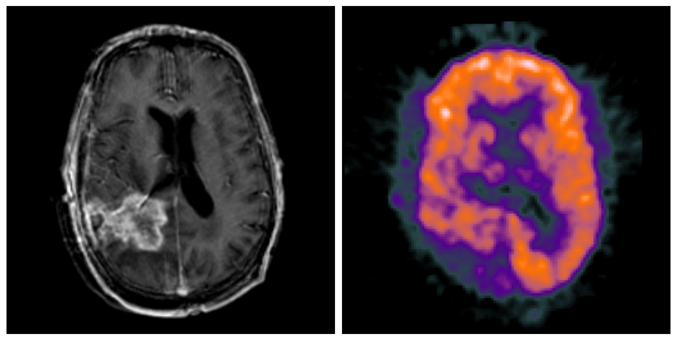

Figure 4.10: Input Image: MRI and Reference Image : PET.

4. Decomposed Images

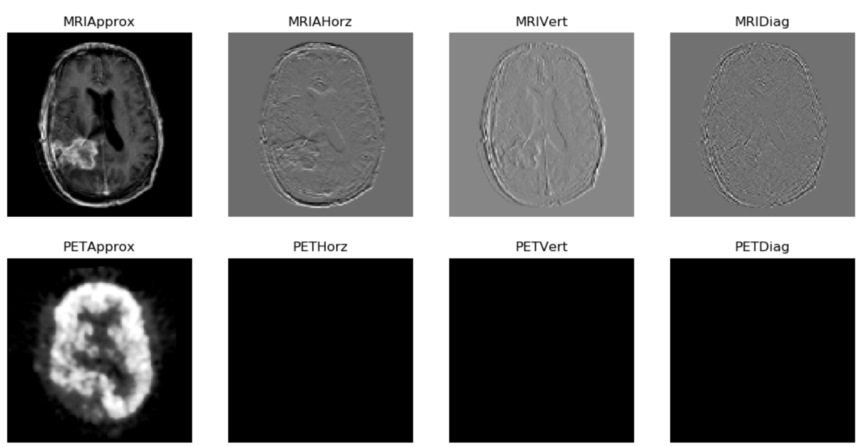

Figure 4.11: single level Decomposed MRI and PET images

4. Fused image

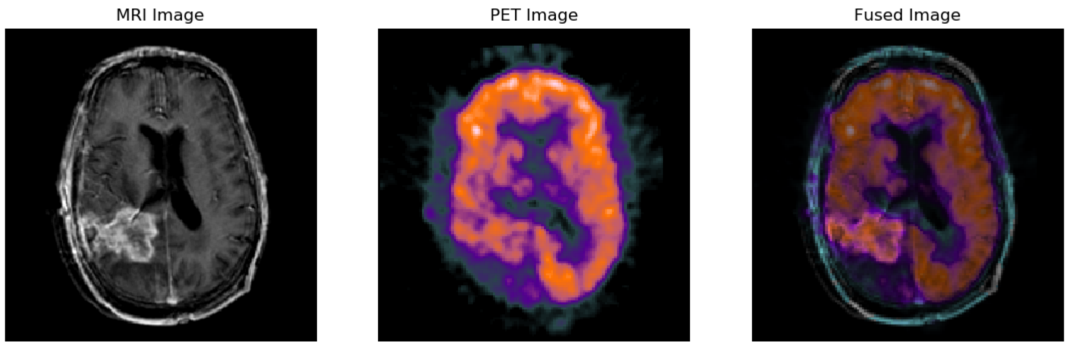

Figure 4.12: Input Images and Fused Image.

Input Images 5

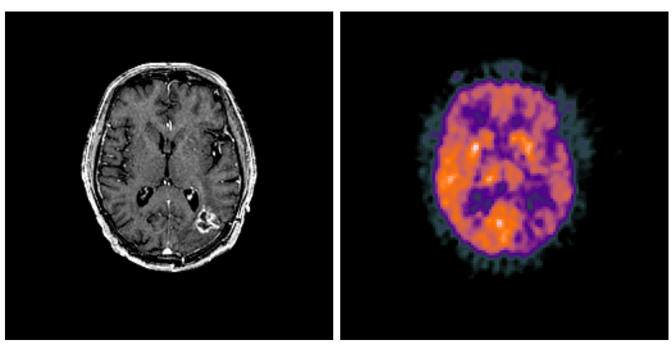

Figure 4.13: Input Image: MRI and Reference Image : PET.

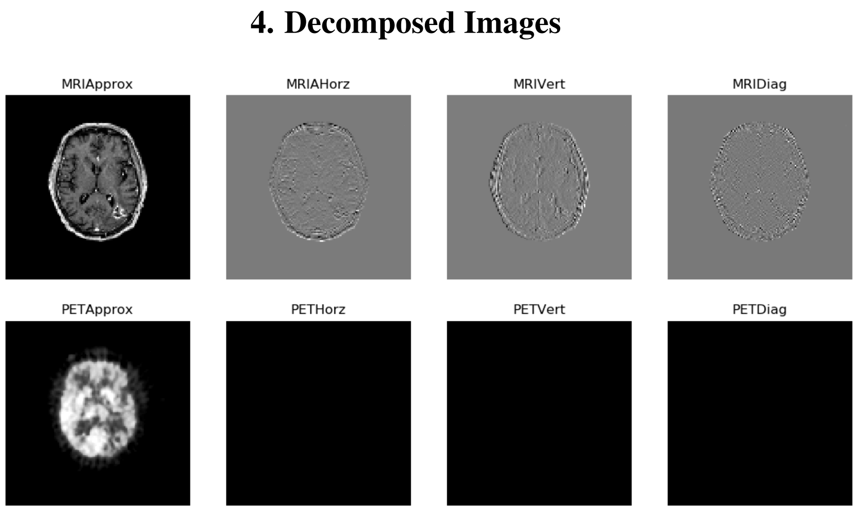

Figure 4.14: single level Decomposed MRI and PET images

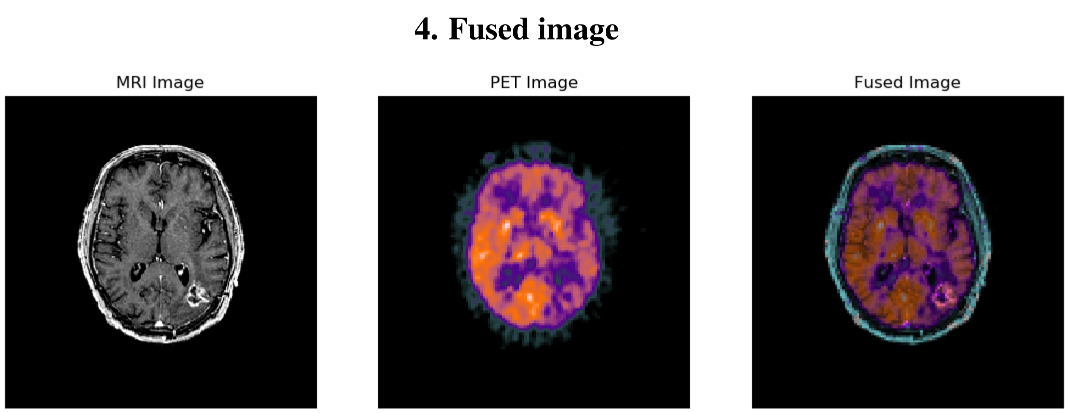

Figure 4.15: Input Images and Fused Image.

Table 4.1: Result table

Image No.	RMSE	MB	SD	PSNR
1	5.78993734	0.88224883	55.01224604	30.59741546
2	6.71853083	1.13398397	47.1711238	31.5853173
3	6.49528685	1.00186284	40.9423686	31.87883690
4	7.41943696	0.74716235	53.62141294	30.72338462
5	7.02894205	1.11867487	47.19739721	31.19300436
6	6.15984331	1.37946699	48.66280022	32.33941030
7	7.10647191	1.10936882	40.76342711	31.09772274
8	6.79853757	1.21477249	53.8015513	31.482493568
9	7.23457626	0.45267853	54.75412689	29.45278561
10	5.34468222	1.39331354	37.8765485	33.572365838

Here the proposed system used 4 factors to ensure its quality, they are RMSE, Mean Bias, Standard Deviation , PSNR.In the above result shows that the RMSE and MB values tends to ”zero” and all others shows higher values. This means the image fusion is accurate.

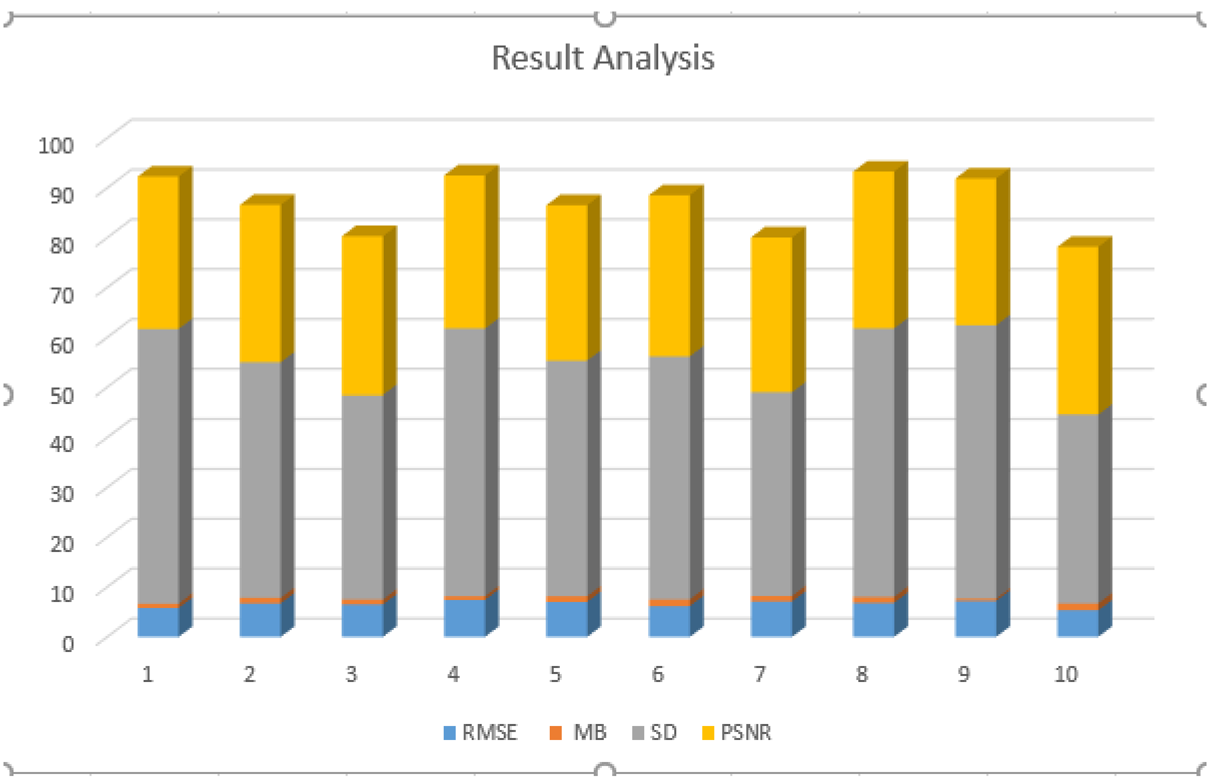

Figure 4.16: Result Analysis: Bar graph

This result shows that the fused image is more accurate in its features.

Chapter 5

CONCLUSION

Images is the simple and easiest way of representing knowledge or information. We can convey messages to anyone using image. No languages is needed for visual communication. So in this time the proposed system makes our images more informative, for that fusion can be used. The proposed system already said about image fusion and its importance above. Also to check the image quality using certain factors.

Atlast it proves that the fusion is more efficient one.

5.1 FUTURE ENHANCEMENT

The project can be extended in future in case of optimization . Here we use flower pollination optimization algorithm for finding optimize fusion weight, but have to define the pollen population. For The population may vary with different images.

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