SIDDAGANGA INSTITUTE OF TECHNOLOGY, TUMAKURU-572103

(An Autonomous Institute Accredited by NBA, NAAC A++, Affiliated to Visvesvaraya Technological University, Belagavi)

Project Report On

" BIOMEDICAL IMAGE FUSION IN WAVELET TRANSFORM DOMAIN"

submitted in fulfillment of the requirement for the completion of VIII semester

BACHELOR OF ENGINEERING

in

ELECTRONICS & TELECOMMUNICATION ENGINEERING

Submitted by

Chinmayee N	(1SI20ET012)
Deepika K J	(1SI20ET015)
Divya A	(1SI20ET016)
Soundarya M	(1SI20ET046)

under the guidance of

Dr. K. VISWANATH

Professor and Head,

Department of ETE

DEPARTMENT OF ELECTRONICS & TELECOMMUNICATION ENGINEERING

2023-24

SIDDAGANGA INSTITUTE OF TECHNOLOGY, TUMAKURU-572103

(An Autonomous Institute Accredited by NBA, NAAC A++, Affiliated to Visvesvaraya Technological University, Belagavi)

DEPARTMENT OF ELECTRONICS & TELECOMMUNICATION ENGINEERING

CERTIFICATE

Certified that the project work entitled " BIOMEDICAL IMAGE FUSION IN TRANSFORM DOMAIN " is a bonafide work carried out by Chinmayee N (1SI20ET012), Deepika K J(1SI20ET015), Divya A (1SI20ET016) and Soundarya M (1SI20ET046) in fulfillment for the completion of VIII semester of Bachelor of Engineering in Electronics & Telecommunication Engineering, Siddaganga Institute of Technology, an autonomous institute under Visvesvaraya Technological University, Belagavi during the academic year 2023-24. It is certified that all the corrections has been incorporated in the report. The Project report has been approved as it satisfies the academic requirements in respect of project work prescribed for the Bachelor of Engineering degree.

Guide **Head of the Department** **Principal**

Dr. K Viswanath
Professor and Head
SIT,Tumakuru-03

ACKNOWLEDGEMENT

We offer our humble pranams at the lotus feet of **His** Holiness, **Dr. Sree Sree Sivakumara Swamigalu**, Founder President and **His** Holiness, **Sree Sree Siddalinga Swamigalu**, President, Sree Siddaganga Education Society, Sree Siddaganga Math for bestowing upon their blessings.

We deem it as a privilege to thank **Dr. M N Channabasappa**, Director, SIT, Tumakuru, **Dr. Shivakumaraiah**, CEO, SIT, Tumakuru, and **Dr. S V Dinesh**, Principal, SIT, Tumakuru for fostering an excellent academic environment in this institution, which made this endeavor fruitful.

We would like to express our sincere gratitude to **Dr.K. Viswanath**, Professor and Head, and also guide, Department of ETE, SIT, Tumakuru for his encouragement and valuable suggestions.

We thank all faculty members and supporting staff of Department of Electronics & Telecommunincation Engineering, SIT, Tumakuru for the help, advice and encouragement.

Chinmayee N	(1SI20ET012)
Deepika K J	(1SI20ET015)
Divya A	(1SI20ET016)
Soundarya M	(1SI20ET046)

Abstract

The process of image fusion aims to combine information obtained from different medical imaging devices, such as CT scans and MRI images, to create more comprehensive and informative images. This project explores various transform-based fusion techniques, including the discrete wavelet transform (DWT) and discrete cosine transform (DCT), for image fusion. The quality of the fused images produced by these fusion techniques is evaluated using suitable metrics, with the study indicating that the DWT variance with consistency verification (CV) followed by DWT variance is superior to the DCT-based fusion method. The work highlights the enhanced performance of DWT-based fusion approaches, as they are accurate and can be applied in real-time due to the energy efficiency of DWT principles when handling stationary images. The study suggests that the discrete wavelet transform (DWT) and its variants outperform other methods when applied in image fusion, producing high-quality fused images, particularly in the context of multi-focus medical images.

Wavelet transforms are powerful tools in image fusion. However, the analysis of medical image fusion is still a challenging area of research. Therefore, we propose a multi-scale fusion of multi-modal medical images in the wavelet domain. Medical images are fused at multiple scales using the maximum selection rule, which provides more flexibility and choice in selecting the relevant fused images. The proposed method is experimentally analyzed using several sets of medical images. The fusion results are evaluated subjectively and objectively with existing state-of-the-art fusion methods, including several pyramid and wavelet transform-based fusion techniques. The performance of DWT and DCT is analysed by using metrics such as entropy, mutual information, PSNR, contrast enhancement index and Mean square error. By using this metrics, DWT gives better informtion than DCT. This project concludes DWT is better than DCT.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

In contemporary healthcare, biomedical imaging is essential for diagnosing and tracking various medical disorders. As technology advances, the demand for more accurate and detailed biomedical images has surged. However, the acquisition of high-resolution images often comes at the cost of increased radiation exposure or longer imaging times, raising concerns about patient safety and comfort. Wavelet fusion involves the integration of information from multiple images using wavelet transform, allowing for the creation of a composite image that captures the strengths of each contributing source. This report focuses on the application of a Biomedical Image Fusion in Transform Domain, aiming to provide a comprehensive overview of the methodology and its potential implications in the field of medical imaging. By harnessing the power of wavelet fusion, this approach seeks to improve image quality, reduce noise, and enhance the diagnostic value of biomedical images, ultimately contributing to more accurate and timely medical diagnoses.

In the subsequent sections, this project concentrated into the fundamental principles of wavelet fusion, discuss its relevance in biomedical imaging, explore the challenges associated with image reconstruction, and present the methodology employed in our research. The findings and implications of our study have the potential to revolutionize the field of medical imaging, offering clinicians a valuable tool for improving diagnostic accuracy and patient outcomes.

1.1 Problem Statement

This report aims to investigate and address the challenges in biomedical imaging reconstruction through the development and evaluation of a novel wavelet fusion approach. Current biomedical imaging reconstruction methods often fall short in providing high-resolution images, hindering the ability to discern fine details crucial for accurate analysis and diagnosis. The presence of noise in biomedical images introduces distortions and reduces the overall quality of the reconstructed images, impacting the reliability of diagnostic information. The complexity of biological structures demands precise representation in reconstructed images. Existing approaches may struggle to faithfully capture and convey the intricate details essential for comprehensive analysis and understanding in the biomedical field.

1.2 Motivation

- Conventional medical imaging faces the challenge of balancing resolution and patient safety, where achieving higher resolution often involves increased radiation exposure or prolonged examination times.

- The compromise in traditional imaging raises significant concerns in the medical community, prompting a search for innovative solutions that can reconcile the trade-off between image quality and patient well-being.

- The motivation for this report lies in the potential of a Biomedical Image Wavelet Fusion Approach to revolutionize image reconstruction in medical diagnostics.

- Leveraging the inherent advantages of wavelet transformations, such as multi-resolution analysis and edge preservation, this approach aims to enhance the quality of biomedical images without compromising patient safety or diagnostic efficiency.

- The ultimate goal is to provide clinicians with a powerful tool that not only improves image resolution and reduces noise but also streamlines the diagnostic process, contributing to the ongoing evolution of biomedical imaging and addressing critical issues in medical diagnostics.

1.3 Objectives of the project

- The primary objective of this research is to develop and implement a Biomedical Image Wavelet Fusion Approach that significantly improves the resolution and overall quality of medical images.

- To Propose and develop a new fusion methodology for multi-view images, based on the discrete wavelet transform and exploiting its scale and orientation decomposition capabilities to integrate in a single volume the acquired views.

- To apply the proposed fusion method for multi-view images enhancement magnetic resonance imaging datasets of the heart study the clinical applicability of the resulting volumes to the diagnostic and therapeutic person of ventricular tachycardia.

1.4 Organisation of the report

Chapter 2 This chapter contains the literature survey and an overview of previously published works related to this project.

Chapter 3 In this chapter system overview is described.

Chapter 4 This chapter describes the software used, algorithm, and flowchart of the project.

Chapter 5 This chapter describes the design equations and the methodology of the project.

Chapter 6 This chapter contains the evaluation criteria and experimental results of the project.

Chapter 7 This chapter contains the conclusion of the project.

Chapter 2

Literature Survey

[1] Sruthy S, Dr. Latha Parameswaran Ajeesh P Sasi, "Image Fusion Technique using DTCWT ", This paper focuses on the process of Image Fusion. Image Fusion is the combination of information from two or more images to create a single image that retains all important features of the original images. The input to the Image Fusion process is a set of images taken from different modalities of the same scene. The output is a better-quality image that depends on a particular application. The objective of Image Fusion is to generate an image that describes a scene better or even higher than any single image by considering their relevant properties, providing an informative image in the process.

[2] V.S. Petrovic and C. S. Xydeas, "Gradient-based multiresolution image fusion," This process presents a new approach to multiresolution signal-level image fusion. Its purpose is to transfer visual information from multiple input image signals into a single fused image without any loss of information or distortion. The system utilizes a unique fusion/decomposition system architecture that employs a "fuse-then-decompose" technique. The information fusion is performed on a multiresolution gradient map representation domain of image signal information.

[3] S. L. Cheng, J. M. He, and Z. W. Lv, "Medical image of PET/CT weighted fusion based on wavelet transform," This paper discusses Image Fusion, an information-integrated technology that has become increasingly popular in various fields. In the medical industry, the PET/CT machine enables in-machine fusion. The fusion image not only provides precise location of pathological changes like CT but also detects the pathological changes as early as possible like PET. However, the within-machine fusion equipment is very expensive, which results in a high fee.

[4] P. S. Pradhan, R. L. King, N. H. Younan, and D. W. Holcomb, "Estimation of the number of decomposition levels for a wavelet-based multiresolution multisensor image fusion"

The following paper describes a popular wavelet-based method for merging multispectral (MS) and panchromatic (PAN) imagery. This method is favored for its ability to maintain the spectral fidelity of the MS imagery while enhancing its spatial quality, which is crucial for automated classification. The quality of the resulting merged images in wavelet-based fusion depends on the number of decomposition levels used in the wavelet transform. If too few decomposition levels are used, the quality of the merged images will be low.

[5] K. Amolins, Y.Zhang, and P.Dare, "Wavelet-based image fusion techniques—an introduction, review, and comparison", This paper explains the process of image fusion, which involves merging two or more images in a way that preserves the most desirable attributes of each. When a panchromatic image is combined with multispectral imagery, the goal is to create an image that has the spatial resolution and quality of the panchromatic image, as well as the spectral resolution and quality of the multispectral image.

[6] S. Garg, K. U. Kiran, R. Mohan, and U. S. Tiwary, "Multilevel medical image fusion using segmented image by level set evolution with region competition," This paper investigates the potential of utilizing segmented image fusion techniques with region competition via level set evolution, particularly in the field of medical imaging.This paper discusses the use of level set evolution with region competition for segmented image fusion in medical imaging.

[7] F. Nencini, A. Garzelli, S. Baronti, L. Alparone, "Estimation Remote sensing image fusion using the curvelet transform,“ This paper examines the use of the curvelet transform in remote sensing image fusion. Remote sensing image fusion is a process of merging information from multiple images of the same scene acquired through different sensors or modalities. The goal is to create a composite image that presents a more comprehensive view of the scene than any of the individual images could provide on their own.

[8] K. Amolins, Y. Zhang, and P. Dare, "Wavelet-based image fusion techniques introduction, review, and comparison," This paper provides an overview of wavelet-based image fusion techniques that involve combining information from multiple images using wavelet transforms.

Chapter 3

System Overview

The Biomedical image wavelet fusion approaches is a methodology is used to improves qualities and diagnostics usefulness of biomedical images. This system uses wavelet fusion techniques to combine information's from various sources, creating a fused images that retaining the strengths of contributing datasets.

We have compared various evaluation metrics of Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) biomedical images to determine their effectiveness.

3.1 Data Acquisitions

This processes beginning with the acquiring of biomedical images. The data is acquiring from various modalities such as X-rays, MRI's, CT-scan, and other modalities. These data images enhances the informations available for wavelet- fusion, resulting in fused images.

3.2 Preprocessing

Before applying the wavelet-fusion approaches, biomedical-images are first given to a pre-processing steps to address any noise, artifacts,and inconsistencies. This step is very crucial in ensuring that input-data is of good quality and reliable. Some preprocessing techniques that includes de-noising, contrast- enhancements, and geometric-corrections.

3.3 Wavelet Transformations

The heart of the system lies in the applications of wavelet-transformations to the pre-processed images. Wavelet transforms enables multi-resolution analysis, breakdown the images into different frequency-components. This decomposition facilitates the identification and preservation of important features, contributing to the overall effectiveness of the fusion process.

3.4 Fusion Algorithms

The fusion algorithms are the critical components responsible for combination of the wavelet coefficients from multiple images. This algorithm determines how the informations from input images and it is integrated to create a fused image. The common fusion techniques includes pixel based fusion, feature based fusion, and hybrid fusion method approaches. The choices of the fusion algorithms was guided by specific requirements of biomedical imaging tasks.

3.5 Validation and Evaluation

The systems effectiveness is rigorously assessed through validations and evaluations processes. Quantitative matrices, such as signal-to-noise ratio, contrast enhancement index, and mutual information,are employed to objectively measures the performance of the fused images..

Chapter 4

Software Implementation

4.1 About Software Requirements

MATLAB is most power full platforms that catering to the specific- requirement of biomedical image-processing. It's comprehensive suites of tools, including Image-Processing Toolboxes,facilitates seamless acquisition, enhancement,and analysis of biomedical images. MATLAB enables the users to employs advanced algorithms for image-segmentation, feature extractions, and classifications, crucial steps in deciphering intricating structures within medical-images.MATLAB was very useful in present scenarios. It's comprehensive suites of tools, including the Image-Processing Toolboxes,facilitates seamless acquisition,enhancement, and analysis of biomedical images.The platform's interactive environment allows for efficient exploration and manipulation of data, while integration with other toolboxes, such as the Computer Vision Toolboxes and Statistics and Machine Learning Toolboxes enhances its capabilities. MATLAB's user friendly interfaces, extensive-documentations, and continuous updates make it an ideal choices for researcher and practitioner in biomedical field, providing a robust foundation for innovation and accurate image processing work of flows.

4.2 About Algorithm

1. Read the images I1 and find sizes.
2. Read the images I2 and find sizes.
3. Compare I1 and I2 in order to makes equal sizes images output will be indexed image.
4. Indexed images should be DICOM(Digital Imaging and Communication of medical).
5. Performing multi-level decomposition using any wavelet transforms.
6. Generating coefficients matrices of level-2 approximations.

7. Fuses wavelets co-efficients using Discrete wavelet transformation.

8. Generates final-matrix of fused wavelet co-efficients.

9. Perform Inverse wavelet transformation to get fused image.

10. Finally,‘computing the entropy,PSNR,MI,CEI and displayed fused images.

4.3 About Flowchart

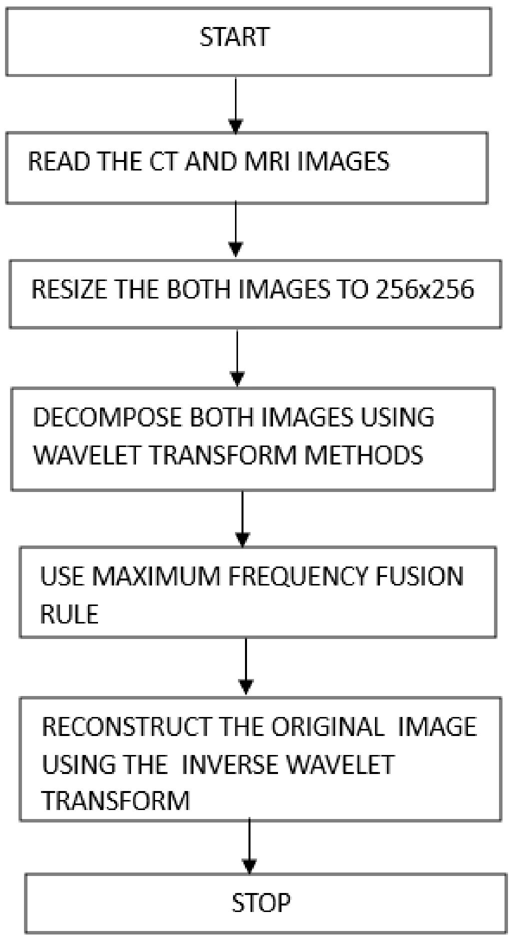


Figure 4.1: Flowchart of proposed work

Figure 4.1 refers the flowchart of proposed work for the fusion of the original images using wavelet transformation.

Chapter 5

Design Equations For DWT Implementation

1. Decompose source images using DWT

$$W_1^{(1)}(x,y) = DWT[I_1(x,y)] \tag{5.1}$$

$$W_2^{(1)}(x,y) = DWT[I_2(x,y)] \tag{5.2}$$

where W$^{(1)}, W^{(2)} arethewaveletcoefficientsofsourceimages I_1(x,y) and I_2(x,y) atscaled.$

2. Calculate fused wavelet coefficients W$_F^{(1)}(x,y)$at scaled by following the expression.

$$W_F^{(1)} = W_1^{(1)}(x,y), if |W_1^{(1)}(x,y)| \geq |W_2^{(1)}(x,y)| \tag{5.3}$$

$$W_F^{(1)} = W_2^{(1)}(x,y), if |W_1^{(2)}(x,y)| \geq |W_2^{(1)}(x,y)| \tag{5.4}$$

3. Reconstruct fused image F$^{(1)}(x,y)$at scaled using IDWT

$$F^{(1)}(x,y) = IDWT[W_F^{(1)}(x,y)] \tag{5.5}$$

The wavelet coefficients in the fusion technique can map for the source of images. Where wavelet configuration is done for decomposed images.

Work done

1. Image acqusitions: Image acquisitions is a critical step in the biomedical imaging, and it plays major role in subsequent applications of wavelet fusion approach for image fusion. The choices of imaging modalities and qualities of input images will be influences the effectiveness of fusion processes.

- **Selections of Imaging Modalities:** Biomedical imaging encompasses various modalities, each with its own strengths and limitations. The common modalities includes X-ray's, magnetic resonance imaging (MRI scan), computed tomography (CT scan), positron emission tomography (PET scan), ultrasound, and more.The selection of these modalities depends on specific clinical or research objectives and type of informations needed for accurate diagnosis or analysis.

- **Multimodality Imaging:** Biomedical wavelet-fusion often involves the combination of information from multiple imaging modalities.Different modalities provides the complementary informations about biological tissues or processes, and combining them can result in a more comprehensive understanding of the imaged structures.

- **Image Acquisition Parameters:** Each imaging modality has specific acquisition parameters that need to be carefully set.Parameters such as resolution, field of views, acquisition time, contrast, and slice thickness (in the case of 3D imaging) must be optimized based on the imaging modality and the clinical or research goals.

2. Image Resizes: Resizing images is a crucial aspect of image fusion. It helps ensure that the resulting fused image is clear and visually interpretable. To achieve this, it's essential to have both the CT and MRI images of the same size. This is important because it enables a one-to-one correspondence between the pixel values of the two images. Regarding the biomedical wavelet fusion for image reconstruction, image resizing is a pre-processing step that may be employed to ensure compatibility and consistency among images from different modalities or resolutions. This step aligns the spatial dimensions of the images before applying the wavelet fusion approaches.

- **Motivation for Image Resizing:** Biomedical imaging modalities will produces images with varying resolutions, pixel sizes, and dimensions.To facilitate effective fusion and comparison between these images, it's beneficial to resize them to a common spatial scale.

- **Spatial Alignment:** Resizing ensures that images from different modalities have the same spatial dimensions, making it easier to perform subsequent image processing operations.It helps achieve spatial alignment between images, which is crucial for accurate fusion and meaningful combination of information.

- **Interpolation Methods:** Image resizing is commonly achieved through interpolation methods, where the pixel values in the original image are used to estimate values at the new positions in the resized image. The common interpolation methods include nearest-neighbours, bilinear, bicubic, and more sophisticated algorithms designed for specific imaging characteristics.

3. Wavelet Transforms: A wavelet transformation signals are decomposed into higher-frequency and lower-frequency bands. There are two main types of transforms: discrete and continuous wavelet transforms. The discrete-wavelet-transformation of a dimensional images involves subsampling and recursive-sampling. At each levels, we obtaining three images: HH(containing diagonal-informations in higher frequencies), LH(containing horizontal-informations in higher frequencies), and HL(containing vertical- informations in higher frequencies). This decomposition produces one approximation image called as LL(low-frequency information). The input images, such as CT-scan and MRI-scan, are subjected to DWT(it is a local transformations from the time and frequency domains and easily generates a varieties of different resolution images). It decomposes the image into different sub-band images, namely, LL,LH,HL,and HH. A higher-frequency subband contains the edge information of the input image, and an LL subband contains clear information about the images, enhancing the appearances of an images with the help of this sub-band information for the fusion process. The clarity-based selection algorithm can be used to fuses the higher-frequency coefficients obtained from the input images and the higher-frequency enhanced coefficients. The lower-frequency coefficients obtained from the input images and the lower-frequency enhanced coefficients can be fused in terms of the weighted fusion algorithms. Carry an inverse discrete wavelet transforms on the fused

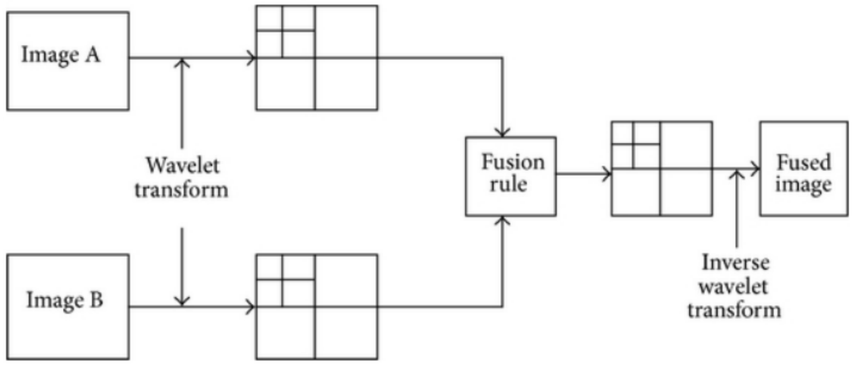


Figure 5.1: Fusion of wavelet transforms of Images

decomposed levels for reconstruction of the final fused images. 2-Dimensional DWT is very useful for image-processing because the image data are discrete and the spatial-spectral resolution is depends on the frequencies. The DWT has the property that the spatial resolutions are small in lower-frequency bands but large in higher-frequency bands. The left-top sub-images(the band with the lowest frequencies) has the smallest spatial resolution and represents the approximation information of the input images. Thus, the DWT is suitable for image-compression. In contrast, the other sub-images (the bands with high-frequencies) show the detailed information of the original image. Therefore, these sub-images can be used for edge detection or corner detection.

Wavelet fusion approach can be done by following methods:

1. Discrete Wavelet Transformation (DWT)
2. Discrete Cosine Transformation (DCT)

1. Discrete Wavelet Transformation (DWT)

The Discrete-Wavelet-Transformation (DWT) can covers the images from spatial area to recurrence spaces. The images can be decomposed by utilising vertical and level lines. The lines spoke to as the primary request of DWT; the images can be decomposed with four sections, for example, the LL1,LH1,HL1 and HH1. The four sections spoke to the four frequencies for the territories in the images. The low recurrence spaces LL1 is more delicated with human eyes. The insight about the higher-frequency coefficients areas LH1,HL1 and HH1 characterised as more detail.

The wavelet changes can plays out the principal wellspring of images, which can create a combination that includes delineate on principles set. The wavelet coefficients in the fusion techniques can map for the input images. This technique helps in the fusion decision map. Finally, the result of inverse wavelet transforms is the fused image.

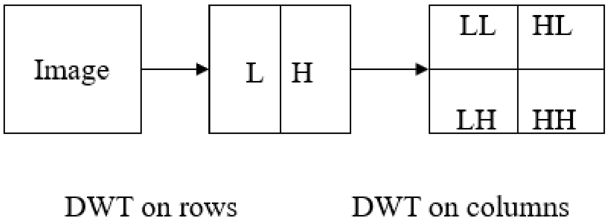


Figure 5.2: Decomposition by DWT

Figure 5.2 shows the decompositions by DWT.In wavelet transformation signals are decomposed, with each levels that is higher-frequency and lower-frequency bands. In discrete wavelet transforms of two-dimensional images involve subsampling and recursive sampling. At each level we obtain three images as HH (containing diagonal information in high frequency), LH (containing horizontal information in high frequency) and HL (containing vertical information in high frequency). These decomposition produces one approximation image known as LL (low frequency information). By using recursively process LL subband can be achieved.

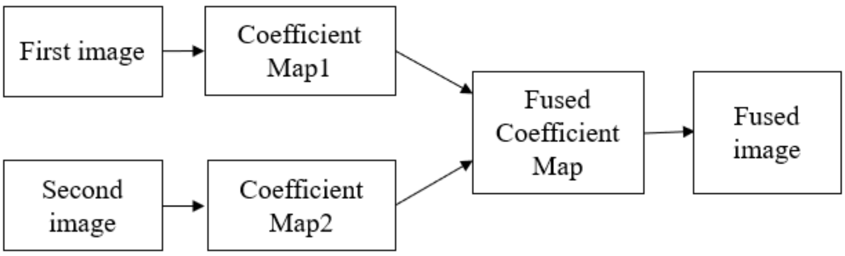


Figure 5.3: Block diagram of DWT based image fusion

Figure 5.3 shows the discrete wavelet transforms done in the first stage. The first image and second image taken for the analysis. In the first image the coefficients of map 1 and coefficients of map 2 were combined to form the fused coefficient map image. The fused image composed of fused coefficient drawn from the IDWT. The first step is to acquires the two images to be fused. The next step is to resize both the images into the same size and applying a DWT to those images and fusion rule is applied to those wavelet coefficients in order to obtain the fused image.

2. Discrete cosine Transformation (DCT)

The Discrete Cosine Transform(DCT) is a crucial tool in image processing, widely acknowledging by the researchers. It has excellent energy compactness properties due to large DCT coefficients being concentrated in the lower-frequency regions. Higher-frequency coefficients are usually contributed by edges. Smooth regions, on the other hand, mostly contributed to DC coefficients. Edges in the spatial domain can only contributing energy to a minimum number of AC coefficients. The DCT is a mathematical techniques that transforms spatial-domain data, like image pixel values, into frequency-domain data. This transformations enables the analysis of frequency components present in the signal, which is known as Frequency Transformation.

Image resizing methods in DCT domain are:

2.1. Down sampling

2.2. Up sampling

2.1 Down sampling

The image is divided into non-overlapping blocks of size 8x8. Each block is transformed into a DCT domain. From each 8x8 DCT block, 4x4 low-frequency (LF) coefficients Ii (m,n), 0 ¡= m,n ¡= 3, i = 1,2,...,4 are extracted. These Lower-frequency coefficients are transformed back to the spatial domain using a 4x4 IDCT to achieves downsampling. This process is known as the reduction function, where four consecutive 8x8 blocks are converted into four consecutive 4x4 blocks in the spatial domain. If further downsampling is desired, the same procedures can be repeated on resulting spatial domain images. Downsampling in DCT may involves subsampling the selected coefficients, which means that only a fractions of the coefficients are retained while the rest are discarded. This further reduces the amount of data required to represent the images is called subsampling.

To reconstruct the downsampled images, the retained DCT coefficients are used to performs the inverse DCT transforms. This converts the frequency-domain coefficients back to the spatial domain, producing the downsampled images.

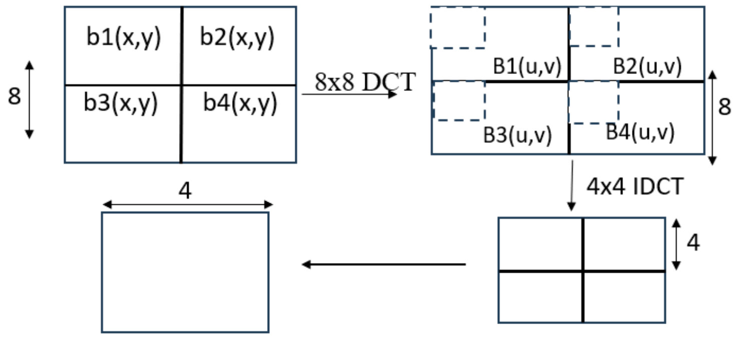


Figure 5.4: Block diagram of downsampling images

2.2 Up sampling

To up-sample images by factors of two, we can divide images into 4x4 blocks. Then, we transform four consecutive 4x4 blocks into the Discrete Cosine Transform (DCT) domain, which are treated as lower-frequency (LF) coefficients. We use these Lower-frequency coefficients as the Lower-frequency components in the 8x8 blocks, while the remaining higher-frequency(HF) coefficients are assumed to be zero. Next, we converted consecutive 8x8 blocks in the DCT domain into the spatial domains by applying an 8x8 Inverse Discrete Cosine Transform (IDCT). This procedure is called the "expand" function.
One common technique for upsampling in DCT involves zero-padding the frequency coefficients. In this approach, additional zero-valued coefficients are inserted between existing ones, effectively increasing the spatial resolution. This technique is known as "zero-padding."

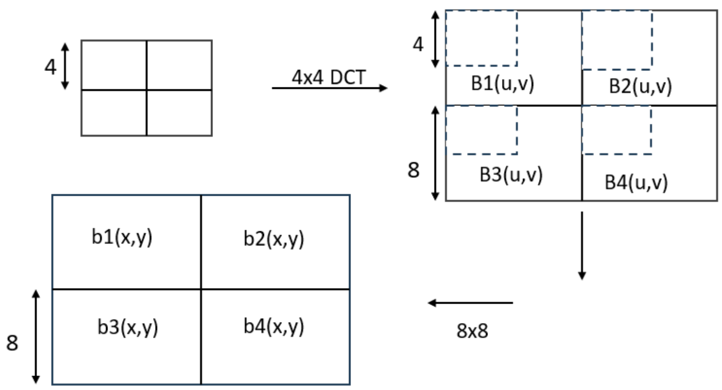


Figure 5.5: Block diagram of upsampling image

Chapter 6

Evaluation Criteria

1. Peak-signal noise ratio(PSNR)

$$PSNR = 10log_{10}(MAX^2/MSE) \tag{6.1}$$

It is the ratio of the reference signal and distortion signal in the images. It is given in dB. The higher the PSNR the closer the distorted image is to the original. MAX is the maximum possible pixel value of the image=256 for 8- -bits/sample. MSE is the average square difference between the reference image and the distorted image. It is computed by pixel by pixel by adding up the squared difference of all the pixels and divided by the total pixel count.

2. Entropy

$$Entropy(H) = \sum_{i=1}^{G} P(i)log_2(P(di)) \tag{6.2}$$

G=Number of possible grayscale level

P(di)=probability of occurrence of a particular gray level.

Entropy is a measure of the amount of information contained in a signal. It can be used to determine the average information content of an image. The maximum entropy value can be achieved when each gray level of the entire image has the same frequency. If the entropy of the fused image is higher than that of the parent image, it indicates that the fused image contains more information.

3. Mean Square Error(MSE)

$$MSE = \frac{1}{MN}\sum_{i=0}^{M}\sum_{j=0}^{N}(I_r(i,j)) - I_f(i,j))^2 \tag{6.3}$$

where M=number of rows

N=number of columns

(i,j)=pixel index

I=given image

I(i,j)=gray value at pixel

It is a metric computed as the root mean square error of the corresponding pixels in the reference image I_rnd the fused image I_f. These metrics will be nearly zero when the reference and fused images are similar. This will increase when the dissimilarities increase.

4. Mutual Information(MI)

$$I(x,y) = \sum_{x \in X} \sum_{y \in Y} P(x,y) log \frac{P(x,y)}{P(x)P(y)} \tag{6.4}$$

Mutual information is a quality that measures a relationship between two random variables that are sampled simultaneously. In particular, it measures how much information is communicated, on average in one random variable about another.

In this definition, P(X) and P(Y) are marginal distributions of X and Y obtained through the marginalization process described in the probability review document.

5. Contrast Enhancement Index(CEI)

$$CEI = (C_i - B_i)/N * M \tag{6.5}$$

where, $C_i$is the pixel value of the fused image at position i

$B_i$is the pixel value of the base image at position i

N is the number of rows in the image

M is the number of columns in the image

Contrast enhancement index (CEI) is a metric used to assess the improvement in contrast achieved through image fusion. It helps to quantify the improvement in contrast between different regions of the fused images.

Experimental Results and Analysis

There are two primary methods of analysis: visual analysis and mathematical analysis.

6.1 Visual Analysis

By using wavelet transform we can observe the edges of the fused image which is very useful for correct diagnosis. These visual images obtained from medical imaging modalities provide valuable information to healthcare professionals for diagnosing diseases, planning treatments, and monitoring patient progress. They can reveal anatomical structures, functional abnormalities, blood flow patterns, and metabolic activities in the delivery of personalized and effective medical care. This is shown in table 6.1 and table 6.2.

6.2 Mathematical Analysis

In this analysis we consider the five parameters entropy, mutual information, PSNR, mean square error, and contrast enhancement index for comparison point of view for fused images and original images. Here we take the reference of normal patient's images with abnormal patients. This is shown in table 6.3.

Table-1: Visual analysis of DWT

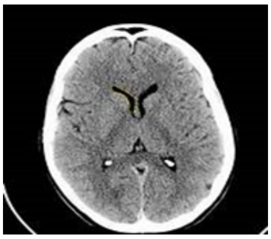
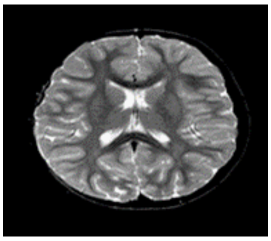
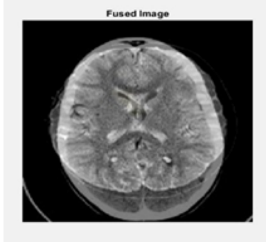
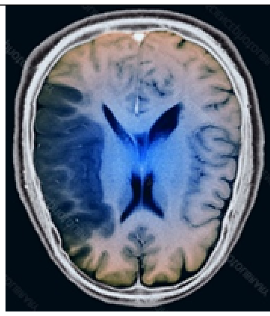
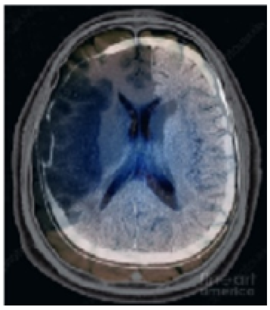
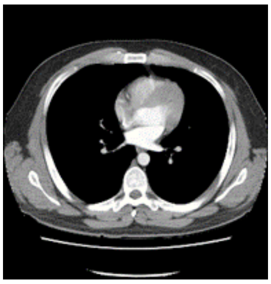
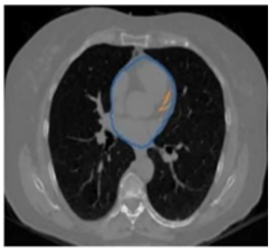
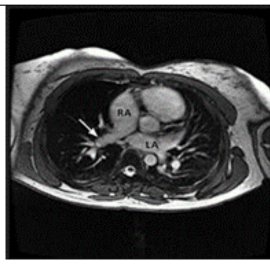
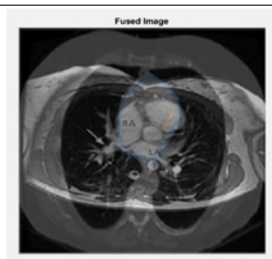
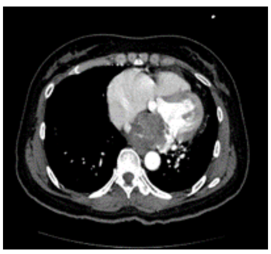
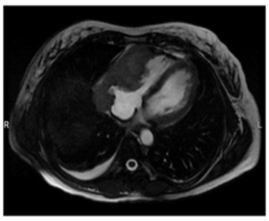
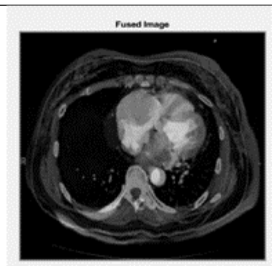
IMAGES	CT IMAGE	MRI IMAGE	FUSED IMAGE
NORMAL BRAIN IMAGES			
BRAIN STROKE IMAGES			
NORMAL HEART IMAGES			
HEART ATTACK IMAGES			
HEART TUMOR IMAGES			

Table 6.1: Visual Analysis of DWT

Table-2: Visual analysis of DCT

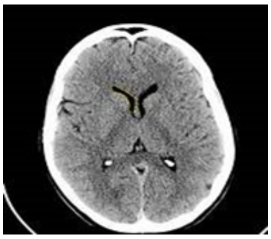
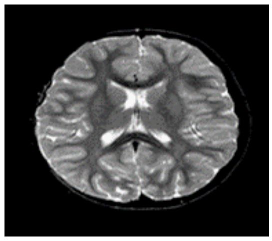
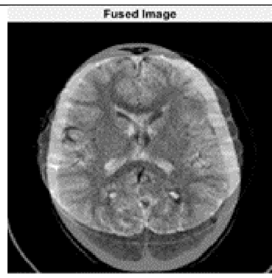
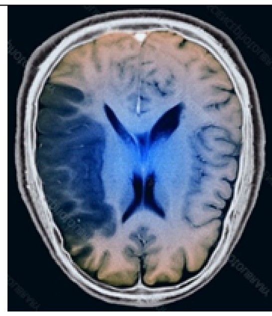
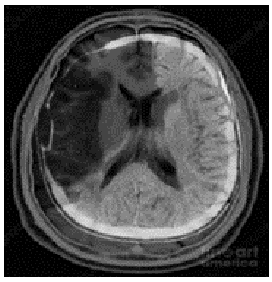
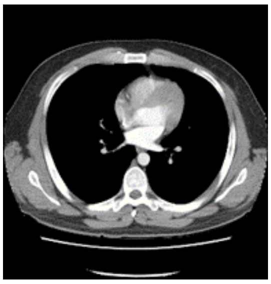
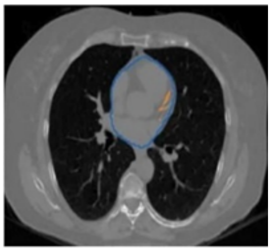
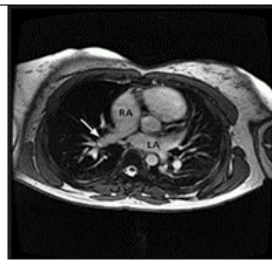
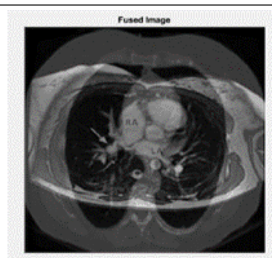
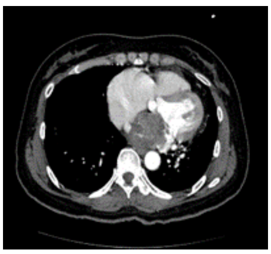
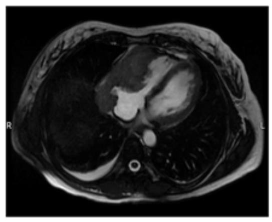
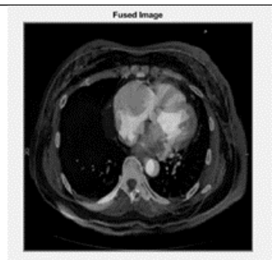
IMAGES	CT IMAGE	MRI IMAGE	FUSED IMAGE
NORMAL BRAIN IMAGES			
BRAIN STROKE IMAGES			
NORMAL HEART IMAGES			
HEART ATTACK IMAGES			
HEART TUMOR IMAGES			

Table 6.2: Visual Analysis of DCT

Table-3: Mathematical analysis of DWT and DCT

Images	Techniques	Entropy	MI	PSNR	MSE	CEI
Normal brain images	DWT	3.1437	2.5664	316.16	0.00098424	1.0035
	DCT	0.87058	1.9069	313.0395	0.22005	0.75262
Brain stroke images	DWT	4.3801	2.3583	319.3659	0.051874	0.72083
	DCT	0.99746	1.3077	311.6095	0.23905	1.0075
Normal heart images	DWT	0.4297	3.1523	318.7675	0.000	0.95011
	DCT	0.48927	2.1425	315.504	0.27888	0.96169
Heart attack images	DWT	3.627	2.2776	320.5131	0.385	0.87917
	DCT	0.022814	1.3525	317.4903	0.20687	1.5585
Heart tumor images	DWT	3.1234	2.2312	323.1609	5.6591	1.1118
	DCT	0.99094	1.3454	312.3848	0.087417	5.1783

Table 6.3: Mathematical Analysis of DWT and DCT

Chapter 7

Conclusions

The different transform domains are used for the fusion of CT and MRI images to get a correct diagnosis of the affected part of the body by observing the edges which are not observed in the MRI and CT images.

This project is evaluated in both visual and mathematical analyses using reference images. In the visual analysis, the edges in a fused image which can be used for accurate diagnosis. In the mathematical analysis, the amount of information carried from the input images to the fused images can be determined. Biomedical image fusion has great potential for improving diagnostic accuracy and providing comprehensive medical assessments. This synergistic approach facilitates better localization, characterization, and monitoring of diseases, ultimately contributing to improved patient care and treatment planning in healthcare. This approach holds a promise for enhancing diagnostic accuracy, facilitating clearer visualization, and contributing to the advancement of medical research and applications.

Bibliography

[1] Sruthy S, Dr. Latha Parameswaran Ajeesh P Sasi, "*Image Fusion Technique using DTCWT*", IEEE 978-1-4673-5090-7/13/2013.

[2] V. S. Petrovic and C. S. Xydeas, "Gradient - based multiresolution image fusion," *IEEE Transcation on Image Processing, vol. 13, no. 2, pp. 228-237, 2004.*

[3] S. L. Cheng, J. M. he, and Z. W. Lv, " Medical image of PET/CT weighted fusion based on wavelet transform," in Proceedings of the 2nd Internationl Conference on Bioinformatics and Biomedical Engineering (iCBBE '08), pp. 2523-2525, 2008.

[4] P. S. Pradhan, R. L. King, N. H. Younan, and D. W. Holcomb,

" Estimation of the number of decomposition levels for a wavelet-based multiresolution multisensor image fusion," IEEE Transcation on Geoscience and Remote Sensing, vol. 44, no. 12, pp. 3674-3686, 2006.

[5] G. H. Qu, D. L. Zhang, and P. F. Yan, "Medical image fusion by wavelet transform modulus maxima," *Optics Express, vol. 9, no. 4, pp. 184–190, 2001.*

[6] S. Garg, K. U. Kiran, R. Mohan, and U. S. Tiwary, "Multilevel medical image fusion using segmented image by level set evolution with region Competition," *in Proceedings of the 27th Annual International Conference of the IEEE Engineering in Medicine and Biology (EMBS '06), pp. 7680-7683, 2006.*

[7] F. Nencini, A. Garzelli, S. Baronti, L. Alparone, "Estimation Remote sensing image fusion using the curvelet transform," *Inf. Fusion 8 (2007) 143-156, doi:10.1016/ j.inffus.2006.02.001. 2 SPEC. ISS.*

[8] K. Amolins, Y. Zhang, and P. Dare, "Wavelet based image fusion techniques-an introduction, review and comparison," *Journal of Photogrammetry and Remote Sensing, vol. 62, no. 4, pp. 249-263, 2007.*

[9] Yong Yang, Dong Sun Park ,Shuying Huang, Zhijun Fang and Zhengyou Wang, "Wavelet based Approach for Fusing Computed Tomography and Magnetic Resonance Images," *Chinese control and decision conference,pp.5770-5774,2009.*

[10] Rohan Ashok Mandhare, PragatiUpadhyay and Sudha Gupta, "pixel-level image fusion using Broveytransforme and wavelet Transform," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, vol.2, pp.2692-2695, June 2013.*

[11] PareshRawat, SapnaGangrade, PankajVyas, "Implementation of Hybrid Image Fusion Technique Using Wavelet Based Fusion Rules," *International Journal of Computer Technology and Electronics Engineering vol.1, pp.1-5, 2011.*

[12] A. Soma Sekhar and Dr.M.N.Giri Prasad, "A Novel approach of image fusion on MR and CT images using Wavelet transforms," *pp.172-176, 2011.*

[13] SusmithaVekkot, and PanchamShukla, "A Novel architecture for wavelet based Image fusion," *International Science Index, vol.3, pp.356-361, 2009.*

[14] Deron Rodrigues, Hasan Ali Virani and ShajahanKutty, "Multimodal Image Fusion Techniques for Medical Images using Wavelets," *International Journal of Research in Advent Technology, vol.2,,pp.310-313, 2014.*

[15] Cheng Shangli and HE Junmin- LvZhongwei, "Medical Image of PET/CT Weighted Fusion Based on Wavelet Transform," *pp.2523-2525, 2008 .*

[16] Mirajkar PradnyaP.andSachin D. Ruikar, "Image fusion based on stationary wavelet transform," *International Journal of Advanced Engineering Research and Studies, 2013.*

[17] Vishal R Gupta, Mr Vishal Kumar Agarwal and Prof S.L.Tade, "Comparison of Medical Image Fusion Algorithm for Preserving the Edge Information Based on Improved Wavelet Coefficient Contrast," *International Journal of Emerging Technology and Advanced Engineering, vol.2, pp.328-333, July 2012.*

[18] H. H. Wang, "A new multiwavelet-based approach to image fusion," *Journal of Mathematical Imaging and Vision, vol.21, pp.177-192, Sep 2004.*

[19] C.Y. Wen, J.K. Chen, "Multi-resolution image fusion technique and its application to forensic science," *Forensic Science International, vol.140, pp.217–232, 2004.*

[20] B. Hamza, Y. He, K. Hamid, W. Alan, " A multiscale approach to pixel-level image fusion," *Integrated Computer-Aided Engineering 12, no. 2, 2005, pp.135-146.*

Course Outcomes

CO 1 : Identify and formulate the problem through literature survey and knowledge of contemporary engineering technology.

CO 2 : Apply engineering knowledge to arrive at optimal design solutions for solving engineering problems in compliance with the prescribed safety norms/standards taking into consideration environmental concerns.

CO 3 : Select suitable engineering tools, platform, sub-system for solving identified engineering problem.

CO 4 : Implement the proposed solution on the selected platform, considering societal, health issues. Validate the design, analyse and interpret the results using modern tools.

CO 5: Comprehend and prepare documents as per the standard, present effectively the work following professional ethics, interact with target group.

CO 6 : Contribute to the team as a member, lead the diverse team.

CO 7 : Demonstrate engineering and management principles, perform the budget analysis through utilization of the resources (finance, power, area, bandwidth, weight, size, etc)

CO-PO Mapping

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2
CO-1	3	3										2	3	
CO-2			3									2		3
CO-3			3											3
CO-4				3	3	2	2					2		3
CO-5								3		3		2		2
CO-6									3					3
CO-7											2		2	
Average	3	3	3	3	3	2	2	3	3	3	2	2	3	3

Attainment level: - 1: Slight (low) 2: Moderate (medium) 3: Substantial (high)

POs: PO1: Engineering Knowledge, PO2: Problem analysis, PO3: Design/Development of solutions, PO4: Conduct investigations of complex problems, PO5: Modern tool usage, PO6: Engineer and society, PO7: Environment and sustainability, PO8: Ethics, PO9: Individual and team work, PO10: Communication, PO11: Project management and finance, PO12: Lifelong learning