A project report on

MULTIMODAL MEDICAL IMAGE FUSION USING DISCRETE WAVELET TRANSFORM WITH NON-SUBSAMPLED COUNTERLET TRANSFORM HYBRID FUSION ALGORITHM

Submitted in Partial fulfillment of the Requirements for the Award of the Degree of

BACHELOR OF TECHNOLOGY

In

ELECTRONICS & COMMUNICATION ENGINEERING

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Certificate

This is to certify that the project report entitled **"MULTIMODAL MEDICAL IMAGE FUSION USING DISCRETE WAVELET TRANSFORM WITH NON-SUBSAMPLED CONTOURLET TRANSFORM HYBRID FUSION ALGORITHM"**

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NOMENCLATURE

DWT	Discrete Wavelet Transform
DCT	Discrete Cosine Transform
PCA	Principal Component Analysis
MRI	Magnetic resonance Imaging
CT	Computed Tomography
PFB	Pyramid Filter Bank
CT	Contourlet Transform
NSCT	Non subsampled Contourlet Transform
NSP	Non subsampled Pyramid
NSDFB	Non subsampled Directional Filter Bank
IDWT	Inverse Discrete Wavelet Transform
PSNR	Peak Signal to Noise Ratio
SD	Standard Deviation

ABSTRACT

In the decade the multimodality image fusion attracts more concentration due to be an important for the evaluation of the patients' status. The paper proposes an effective method of image fusion. which uses Discrete Wavelet Transform with Non-Subsampled Contourlet Transform. The merging of multiple imaging data of the same patient, acquired at different times and by different modalities, is termed as multimodal fusion. Bringing together anatomical and functional information with sensitivity and specificity gives the true value of multimodal fusion imaging. Its purpose is to attempt to increase the apparent depth of field through the fusion of object within several different fields of focus.

The PCA & DCT are conventional fusion techniques with many drawbacks, whereas DWT based techniques are more favorable as they provide better results for image fusion. In this paper, two algorithms based on DWT are proposed. In PCA information loss is occurred. Where as in DCT the output values are typically real-valued thus we need a quantization step to produce output that is integer-valued.

Now we have to consider different copies of the same part are chosen. The source images are registered and decomposed into low frequency and high frequency coefficients. The low frequency coefficients fused and apply the average fusion rule and high frequency coefficients fused and apply maximum fusion rule. Finally, the paper restructures the final image by inverse transformation of low-frequency and high-frequency components using NSCT and DWT. Experimental results indicate that the method proposed in this paper achieves an improvement in objective evaluation. The traditional and proposed methods are used for the experimental work get the output image. It indicates that the method is effective, practical and good performance.

CHAPTER-1

INTRODUCTION

1.1 Introduction

The advances in sensor technology, microelectronics and communications have brought a need for processing techniques that can effectively combine information from different sources into a single composite for interpretation. Several situations in image processing require high spatial and high spectral resolution in a single image. In image-based application fields, image fusion has emerged as a promising research area. As many sources produce images, image processing has become one of the most important domains for fusion. However, most of the available equipment is not capable of providing this type of data convincingly.

The sensor in the surveillance system can only provide the scenery view in a narrow depth for a particular focus, yet the demanding application of this system requires a clear view with a high depth of the field. Image fusion provides the possibility of combining different sources of information. Similarly, in order to support more accurate clinical information for physicians to deal with medical diagnosis and evaluation, multimodality medical images are needed, such as X-ray, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Magnetic Resonance Angiography (MRA), Positron Emission Tomography (PET), and Single-Photon Emission Computed Tomography (SPECT) images. These multimodality medical images provide complementary and conflicting information. For example, the CT image can provide dense structures like bones and implants with less distortion, but it cannot detect physiological changes, while the MRI image can provide normal and pathological soft tissues information, but it cannot support the bones information (Yang et al. 2010). In this case, only one kind of image may not be sufficient to provide accurate clinical requirements for the physicians. Hence, the fusion of the multimodal medical images is necessary and it has become a promising and very challenging research area in recent years. Another advantage of image fusion is that it can reduce the storage cost by storing the single fused image instead of multisource images.

1.2 Medical Imaging

Medical imaging systems play a significant role in the medical field. They aid doctors in proper diagnosis. Anatomic images of high quality are used for diagnosis of problems in patients. Medical imaging is the process of creating visual representations of the interior of a body for clinical analysis and medical intervention as well as visual representation of the function of some organs or tissues. Medical imaging seeks to reveal internal structures hidden by the skin and bones, as well as to diagnose and treat diseases. Medical imaging also establishes a database of normal anatomy and physiology to make it possible to identify abnormalities.

Different imaging techniques are available to acquire images of the human body. It is a part of biological imaging and incorporates radiology which uses the imaging technologies of X-ray radiography, CT, MRI, medical ultrasonography or ultrasound, and nuclear medicine functional imaging techniques such as PET and SPECT.

1.3 Imaging Modalities

In the clinical context, invisible light medical imaging is generally equated to either clinical imaging or radiology. The medical practitioner responsible for interpreting the images is a radiologist. Visible light medical imaging involves either digital video or still pictures that can be seen without special equipment. Dermatology and wound care are two modalities that use visible light imagery. Diagnostic radiography designates the technical aspects of medical imaging and in particular the acquisition of medical images. The radiologic technologist is responsible for acquiring medical images of diagnostic quality, although some radiological interventions are performed by radiologists. Many of the techniques developed for medical imaging also have scientific and industrial applications (James & Dasarathy 2014).

1.3.1 Medical Radiography

Two forms of radiographic images are in use in medical imaging; projection radiography and fluoroscopy, with the latter being useful for catheter guidance. This imaging modality utilizes a wide beam of X rays for image acquisition and is the first imaging technique available in modern medicine.

Fluoroscopy produces real-time images of internal structures of the body in a similar fashion to radiography, but employs a constant input of X- rays, at a lower dose rate. Contrast media, such as barium, iodine, and air are used to visualize internal organs as they work. Fluoroscopy is also used in image-guided procedures when constant feedback during a procedure is required. An image receptor is required to convert the radiation into an image after it has passed through the area of interest.

Projectional radiographs, more commonly known as X-rays, are often used to determine the type and extent of a fracture as well as for detecting pathological changes in the lungs. With the use of radio-opaque contrast media, such as barium, they can also be used to visualize the structure of the stomach and intestines - this can help to diagnose ulcers and certain types of colon cancer.

1.3.2 Computed Tomography

In CT, a computer processes data received from radiation detectors and computationally constructs an image of the structures being scanned. Imaging techniques using this method are far superior to conventional tomography as they can readily image both soft and hard tissues while conventional tomography is quite poor at imaging soft tissues.

CT is also known as X-ray computed tomography, computer- assisted tomography or Computed Axial Tomography (CAT). It is a helical tomography technique, which traditionally produces a 2D image of the structures in a thin section of the body. In CT, a beam of X-rays spins around an object being examined and is picked up by sensitive radiation detectors after having penetrated the object from multiple angles. A computer then analyses the information received from the scanner's detectors and constructs a detailed image of the object. It has a greater ionizing radiation dose burden than projection radiography. The repeated scans must be limited to avoid health effects. CT is based on the same principles as X-Ray projections but in this case, the patient is enclosed in a surrounding ring of detectors assigned with 500-1000 scintillation detectors (Dhawan 2003).

1.3.3 Magnetic Resonance Imaging

An MRI instrument (MRI scanner), or Nuclear Magnetic Resonance (NMR) imaging scanner uses powerful magnets to polarize and excite hydrogen nuclei of water molecules in human tissue, producing a detectable signal which is spatially encoded, resulting in images of the body. Like CT, MRI traditionally creates a two dimensional image of a thin "slice" of the body and is considered a tomographic imaging technique. Unlike CT, MRI does not involve the use of ionizing radiation and is therefore not associated with the same health hazards. For example, because MRI has only been in use since the early 1980s, there are no known long-term effects of exposure to strong static fields and therefore there is no limit to the number of scans to which an individual can be subjected, in contrast with X-ray and CT. However, there is well-identified health risks associated with tissue heating from exposure to the RF field and the presence of implanted devices in the body, such as pace makers. These risks are strictly controlled as part of the design of the instrument.

The CT and MRI are sensitive to different tissue properties. The appearance of the images obtained with the two techniques differs markedly. In CT, X-rays must be blocked by some form of dense tissue to create an image. Hence, the image quality when looking at soft tissues will be poor. In MRI, while any nucleus with a net nuclear spin can be used, the proton of the hydrogen atom remains the most widely used, especially in the clinical setting, because it is so ubiquitous and returns a large signal. This nucleus, present in water molecules, allows the excellent soft-tissue contrast achievable with MRI (https://en.wikipedia.org/wiki/Medical_imaging).

A number of different pulse sequences can be used for specific MRI diagnostic imaging (multiparametric MRI or mpMRI). It is possible to differentiate tissue characteristics by combining two or more of the following imaging sequences, depending on the information being sought: T1-weighted (T1-MRI), T2-weighted (T2-MRI), Diffusion Weighted Imaging (DWI-MRI), Dynamic Contrast Enhancement (DCE-MRI), and Spectroscopy (MRI-S). For example, imaging of prostate tumors is better accomplished using T2-MRI and DWI-MRI than T2-weighted imaging alone (http://sperling prostatecenter.com). The number of applications of mpMRI for detecting disease in various organs continues to expand, including liver studies, breast tumors, pancreatic tumors, and assessing the effects of vascular disruption agents on cancer tumors.

1.3.4 Nuclear Medicine

Nuclear medicine encompasses both diagnostic imaging and treatment of disease, and may also be referred to as molecular medicine or molecular imaging and therapeutics (https://www.snmmi.org). Nuclear medicine uses certain properties of isotopes and the energetic particles emitted from radioactive material to diagnose or treat various pathology. Different from the typical concept of anatomic radiology, nuclear medicine enables assessment of physiology. This function-based approach to medical evaluation has useful applications in most subspecialties, notably oncology, neurology, and cardiology. Gamma cameras and PET scanners are used in scintigraphy, SPECT and PET to detect regions of biologic activity that may be associated with disease.

PET images can be viewed in comparison to CT scans to determine an anatomic correlation. Modern scanners may integrate PET, allowing PET- CT, or PET-MRI to optimize the image reconstruction involved with positron imaging. This is performed on the same equipment without physically moving the patient off of the gantry. The resultant hybrid of functional and anatomic imaging information is a useful tool in non-invasive diagnosis and patient management (Luna et al. 2014).

1.4 Image Fusion

Image fusion is broadly defined as the process of integrating complementary and redundant information from two or more different images into one composite image which contains enhanced information from the individual source images. The original information should be preserved and the artifacts should be minimized in the fused image. The principal motivation for image fusion is to improve the quality of the information contained in the composite image (Mitchell 2010). Due to this reason, image fusion has become interesting area for many researchers.

Image fusion is widely used in many fields such as medical imaging, remote sensing, microscopic imaging, concealed weapon detection, robotics, machine vision and military applications. Image fusion creates new images which are more suitable for human and machine perception, and for further image processing tasks. The image fusion is not a minor process due to the following reasons (Ellmauthaler et al. 2013).

- The source images may come from different types of sensors with different dynamic range and resolution.
- The source images may exhibit complementary information.
- They may show common information with reversed contrast which complicates the image fusion process.

A fusion approach which produces a composite image that appears natural to a human interpreter is highly desirable. In general, the fusion algorithm should have the following requirements (Piella 2003).

- It should preserve all relevant information contained in the input images as closely as possible.
- It should not introduce any artifacts or inconsistencies which can either distract or mislead a human observer or any subsequent image processing tasks.
- It should suppress the irrelevant features contained in the input images.
- It must be reliable, robust and, as much as possible, tolerant of imperfections such as noise or mis registrations.

1.5 Different Levels of Image Fusion

The fusion process can be performed at three different processing levels. They are given below (Zhang & Blum 1999).

- Pixel level image fusion
- Feature level image fusion
- Decision level image fusion

Pixel level image fusion process involves the operation on each and every image pixel. The simplest image fusion algorithm just takes the pixel by pixel average of the source images. However, this leads to undesirable side effects such as reduced contrast. The advantage of pixel level fusion is that the images used contain the original measured quantities and the algorithms are easy to implement and computationally efficient. Hence, pixel level-based fusions are used in most of the image fusion applications. Pixel level image fusion can be helpful for a human observer to detect or recognize potential targets easily.

Feature level image fusion first employs feature extraction, for example, by segmentation procedures, separately on each source image and then performs the fusion based on the extracted features. Those features can be identified by the characteristics such as contrast, shape, size and textures. These similar features are fused from input images. However, the region-level image fusion performance depends highly on the quality of the segmentation process. The segmentation errors such as over-segmentation or under- segmentation may lead to the degradation of certain features in the fused image.

Decision level fusion allows the information from multiple images to be effectively merged at the higher level of abstraction. The input images are usually processed individually for information extraction and classification. The obtained information can be combined by applying decision rules to reinforce common interpretation.

The choice of the appropriate image fusion level depends on the applications. There exists a strong inter-linkage between the different levels of image fusion. Many fusion rules are used to determine the individual pixels in the composite image at pixel-level. The same rules can also be used at region- level to fuse the extracted features.

Further, decision-level fusion can use the segmentation map created at region-level for decision-making. Since the pixel level fusion has the advantage that the images used contain the original measured quantities, and the algorithms are computationally efficient and easy to implement, the most image fusion applications employ pixel level-based methods (Redondo et al. 2008). Hence, fusion of images at pixel-level is mainly concerned in this research work.

1.6 Categorization of Image Fusion

According to images used for fusion and its purpose, image fusion methods can be categorized into five types which are given below (Flusser et al. 2007).

- Multimodal image fusion
- Multiview image fusion
- Multitemporal image fusion
- Multi focus image fusion
- Multi exposure image fusion

In multimodal image fusion, images which are taken from different sensors are fused. Examples: CT and MRI images, visible and infrared images, panchromatic (PAN) and multispectral (MS) satellite images. In multi view image fusion, images which are taken from same sensor and at the same time, but taken from different viewpoints are fused. In multitemporal image fusion, images which are taken from same sensor at different times are fused in order to detect changes between them. In multi focus image fusion, images which are taken from same sensor at various focal lengths are fused. In multi exposure image fusion, images which are captured under different exposure settings are fused.

In this research work, CT, MRI and PET images are taken for conducting experiments on the proposed image fusion techniques. Hence, this research work comes under the multimodal image fusion.

1.7 Image Fusion Approaches

The image fusion techniques are based on two approaches which are given below

(Yang et al. 2008).

- Spatial domain image fusion approach
- Transform domain image fusion approach

1.7.1 Spatial Domain Image Fusion Approach

This approach deals with the pixels of the input images directly. The pixel values are manipulated to achieve desired result. The spatial domain approaches include pixel averaging method, maximum/minimum method, Brovey method, Principal Component Analysis (PCA), Intensity-Hue Saturation (IHS) based methods and high pass filtering based image fusion methods. The disadvantage of spatial domain approaches is that they produce spatial distortion in the fused image (Li & Yang 2008). The spatial distortions are well handled by transform domain approach.

1.7.2 Transform Domain Image Fusion Approach

In this approach, the image in spatial domain is first converted into transform domain. All the fusion operations are performed in the transform domain and then the inverse transform is performed to get the resultant fused image. This approach includes pyramid transform based methods, discrete wavelet transform based methods, curvelet transform based methods, contourlet transform based methods, etc. Image fusion methods range from pixel averaging method to more sophisticated and state-of-art methods such as Multiscale Transform (MST) based image fusion.

Among the transform domain image fusion methods, the most frequently used methods are based on MST which decomposes an image into various scales and directional subbands. The fusion is performed on a number of scales and orientations independently. The usually employed MST are Pyramid Transform (PT), Discrete Wavelet Transform (DWT), Undecimated Wavelet Transform (UWT) also known as Stationary Wavelet Transform (SWT), Dual-Tree Complex Wavelet Transform (DTCWT), Curvelet Transform, Contourlet Transform and Nonsubsampled Contourlet Transform (NSCT).

In recent times, MST also known as Multiscale Geometric Analysis (MGA) tools have become more popular to analyse the information content of the source images for fusion purpose. These tools are primarily based on a mechanism similar to that of a human visual system. As a result, the outputs produced by the image fusion algorithms incorporating these MGA tools are more visually pleasing and are free from traditional drawbacks such as artifacts and reduced contrast.

1.7.2.1 Discrete Wavelet Transform

The most commonly used methods are wavelet-based methods which perform multiresolution decomposition on each source image, and then integrate all these decompositions to form a composite representation and finally reconstruct the fused image by performing an inverse multiresolution transform. Although DWT provides good localization both in time and spatial frequency domain, one of the major drawbacks of DWT is shift variance. This leads to major change in the wavelet coefficients of the image even for small shifts in the input images. In medical imaging, it is important to preserve the exact location of the information. The shift variance may lead to inaccuracies. For example, in medical image fusion, it is needed to preserve edge information, but DWT based fusion may produce specularities along the edges.

1.7.2.2 Nonsubsampled Contourlet Transform

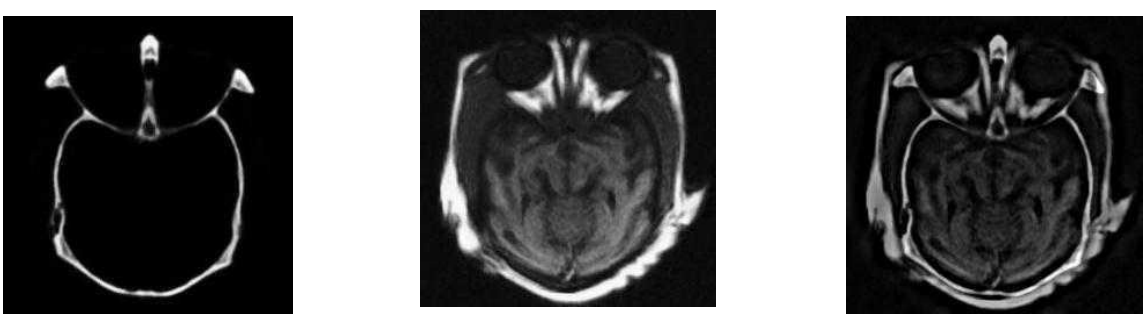
NSCT is a highly effective shift-invariant MST. The unique structure of NSCT, namely, two shift-invariant components, Nonsubsampled Pyramids (NSP) and Nonsubsampled Directional Filter Banks (NSDFB) impart NSCT with shift invariance and redundancy properties, thereby making it as more appropriate MST for image fusion algorithms. The drawback of the conventional NSCT based image fusion algorithms is computationally very expensive, when the image has larger dimensions.

1.8 Applications Of Image Fusion

Image fusion has the important applications in medical imaging, remote sensing, military, and industrial engineering, etc. The benefits of image fusion include improved spatial awareness, increased accuracy in target detection and recognition, and increased system reliability.

1.8.1 Medical Science

With a rapid development in modern instrumentations, medical imaging plays a vital role in a large number of applications including diagnosis, treatment and research. Owing to the technical limitations, the quality of medical images is not usually satisfactory which degrades the accuracy of human interpretation and further medical image analysis. It needs the quality of these images to be enhanced. One method to improve the quality of the image is by image denoising. Another method is by image fusion which enhances the image quality by combining the common and complementary information from multimodal images into a single fused image. Figure 1.1 shows the medical image fusion. The CT image which provides information about bones is fused with MRI which provides information about soft tissues. The resultant fused image has the information about both bones and soft tissues.



(a) **(b)** **(c)**

(Source: Yong Yang et al. 2010)

Figure 1.1 Medical Image Fusion example. (a) CT (b) MRI (c) Fused image

1.8.2 Remote Sensing

Remote sensing is the measurement of object properties on the earth's surface using data acquired from the aircrafts and satellites by meansof optical sensors. Remote sensing image fusion is an effective way to use a large volume of data from multisensor images. Most earth satellites such as SPOT, Landsat 7, IKONOS and Quick Bird satellites provide both PAN images at a higher spatial resolution and MS images at a lower spatial resolution. Many remote sensing applications require both high spatial and high spectral resolutions, especially for Geographic Information Systems (GIS) based applications. An effective image fusion technique can produce such remotely sensed images. In most of the remote sensing applications, due to physical constraints, a trade-off between spectral and spatial resolution has to be accepted. In other words, some satellite sensors supply the spectral bands needed to distinguish some features spectrally but not spatially (MS image), whereas other sensors include the spatial information needed to distinguish features spatially but not spectrally (PAN image). Image fusion merges images from various sensors into a single image which provide both a high spatial and spectral resolution.

1.8.3 Military

Military is appeared as one of the application areas for image fusion. It covers applications such as concealed weapon detection, identification, detection and tracking of targets, mine detection and tactical situation assessment. The thermal and visible images are fused for camouflaged target detection.

1.8.4 Industrial Engineering

Image fusion is used in a wide variety of industrial and civil applications. In robotics, multi-sensor information is used to estimate the position and orientation as well as to navigate a robot in order to avoid collisions and stay on a preset path. Moreover, image fusion is applied in computerized quality management for defect inspection of products. The image fusion can be used to extend the depth of focus of existing image capturing systems. Due to the limited depth-of-focus of individual optical lenses, it is often impossible to get a single image with all objects in focus. One way to overcome this problem is to collect several images from the same scene but with different focus points and combine them into a single composite image which contains the focused regions of all input images. Another application of image fusion in the industrial context is the combination of multi exposure images. A natural scene often has a high dynamic range that exceeds the capture range of common digital cameras. Therefore, a single captured image is usually insufficient to reveal all the details due to under or overexposed regions. To solve this problem, images of the same scene can be captured under different exposure settings and then be combined into a single image using image fusion techniques.

1.9 Motivation For Image Fusion Research

Motivation for image fusion is the result of recent advancements in the medical field. As the new image sensors are available at high resolution, multiple sensors are used in a wide range of imaging applications. These sensors are of high spatial and spectral resolution. The images taken by these sensors are more reliable, informative and contain complete picture of the scanned environment. Thus, they help in improved performance of dedicated imaging systems. Over a period of decade, remote sensing, medical imaging, surveillance systems, etc., are a few applications areas that were benefited by these multi-sensors. A sensor grabs multiple images of a same part and one of them will be considered for analysis. However, the considered image may not have good spatial and spectral resolution. In order to have the image with high spatial and spectral resolution, images can be fused. Hence, this research work identifies the need for image fusion by developing techniques to improve the performance of existing fusion methods. The purpose of image fusion is to enhance the spatial and spectral resolution from low resolution images. Due to this reason, image fusion has become an interesting topic for many researchers.

The successful diagnosis of a disease depends on the accuracy of the image obtained from medical imaging modalities. Medical image fusion acts as a 'life saving tool'-thus it has emerged as a promising research field in recent years. The objective of medical imaging is to acquire a high-resolution image with more information for the sake of diagnostic purposes.

1.10 Problem Statement

Image fusion is used to combine input images of the same scene into a single fused image which preserves full information and also retains the important features from each of the original images. The fused image should have more useful information content compared to the individual input image.

The DWT based image fusion technique which is commonly used has shift variance problem which leads to major change in the wavelet coefficients of the image for small shift in the input images. In medical applications, preservation of edge information is important. Since medical images have several objects and curved shapes, there is a need for an alternative approach which has a high accuracy of edge localization. In order to overcome the shift variance problem, the SWT and NSCT based image fusion techniques are formulated in this research.

1.11 Scope

Multimodal medical image fusion techniques are proposed in this research work using SWT, NSCT, and hybrid SWT-NSCT based image fusion techniques which are used for physicians to diagnosis diseases in clinical applications. It will perform well for all type of image data sets. In this research work, these image fusion techniques are applied to CT, MRI, PET, and SPECT images. All medical image pairs are grey scale images and are of size 256 × 256. The performance parameters mean, standard deviation, average gradient, edge-based similarity measure (QAB/F) are used to evaluate the performance of fusion techniques.

1.12 Objectives

The aim of the image fusion is to integrate distinct and complementary data to enhance the information present in the input images as well as to increase the reliability of the interpretation. The main objectives of this research work are,

- To analyze the conventional fusion methods PCA and DWT for fusion of medical images.
- To integrate the information from multimodality medical images using SWT based image fusion technique by applying canny operator and maximum selection rule as fusion rules in order to overcome the problem of DWT.
- To improve the performance of SWT based image fusion technique using morphological processing and maximum selection rule as fusion rules.
- To surmount the problem of SWT by applying NSCT based image fusion technique using mean and variance-based image fusion rules.
- To integrate SWT and NSCT for fusion of medical images to improve the performance of image fusion technique using spatial frequency and variance-based image fusion rules.

1.13 Organization Of The Thesis

The thesis is composed of seven chapters. It is organized as follows.

Chapter 1 presents the introduction of image fusion, categorization, application and medical imaging.

Chapter 2 describes the literature survey made in the areas of pyramid based, DWT based and NSCT based image fusion techniques.

Chapter 3 It gives the information about the methods that we are used in the implementation of the proposed image fusion method.

Chapter 4 It includes the discussions and the results of the project.

Chapter 5 It provides a summary, conclusion and future improvements of the resent research.

The works of several researchers are quoted and used as evidence to support the concepts explained in the thesis. All such evidences used are listed in the reference section of the thesis.

1.14 Summary

This chapter dealt with concepts of image fusion, levels and categorization of image fusion, medical imaging and different imaging modalities. It also explained the approaches like spatial domain and frequency domain approaches. In addition, this chapter defined the general methodology used for present research work. Furthermore, the phases involved in the research methods have also been discussed.

CHAPTER-2

LITERATURE SURVEY

2.1 Introduction

The image fusion is the process of combining two or more images to form a single fused image which can provide more reliable and accurate information. It is useful for human visual and machine perception or further analysis and image processing tasks. Over the last few decades, medical imaging plays an important role in a large number of healthcare applications including diagnosis, treatment, etc. The main objective of multimodal medical image fusion is to capture the most relevant information from input images into a single output image which is useful in clinical applications. This chapter deals with study of various research works in image fusion techniques that have been used for fusing images.

2.2 Survey On Discrete Wavelet Transform Based Image Fusion

Shi et al. (2005) addressed two issues in image fusion (a) the image fusion method and (b) corresponding quality assessment. Initially, a multi- band wavelet-based image fusion method is presented. This fusion method is applied to a case study to demonstrate its performance in image fusion. Secondly, quality assessment for fused images is discussed. The objectives of image fusion include enhancing the visibility of the image and improving the spatial resolution and the spectral information of the original images. The spatial and spectral resolution, quantity of information, visibility, contrast or details of features of interest are used for assessing the quality of an image after fusion. Quality assessment is application dependent. Based on application, a set of

qualities are classified and analyzed. These sets of qualities included average grey value for representing intensity of an image, standard deviation, information entropy, profile intensity curve for assessing details of fused images, and bias and correlation coefficient for measuring distortion between the original image and fused image in terms of spectral information.

Pradhan et al. (2006) presented wavelet-based scheme for the fusion of MS and PAN images due to its ability to preserve the spectral fidelity of the MS image while improving its spatial quality. The resultant image can be used for automatic classification. Wavelet-based fusion results depend on the number of decomposition levels applied in the wavelet transform. Too many levels reduce the spectral similarity between the original MS and the pan- sharpened images. If the shift-invariant wavelet transform is applied, each excessive decomposition level results in a large computational penalty. Thus, the choice of the number of decomposition levels is significant. PAN and MS image pairs with different resolution ratios are fused using the shift-invariant wavelet transform, and the optimal decomposition levels are determined for each resolution ratio. The fusion of images with larger resolution ratio requires a higher number of decomposition levels.

Zheng et al. (2007) proposed an advanced DWT (aDWT) method that incorporates PCA and morphological processing into a regular DWT fusion algorithm with two adjustable parameters which includes the number of levels of DWT decompositions and the length of the selected wavelet. Results with aDWT are compared to those with a regular DWT and with a Laplacian pyramid. They proposed new metric, called the ratio of Spatial Frequency error (rSFe). Human perceptual assessment was measured and found to support the assertion that the aDWT offers a significant improvement over the DWT and pyramid methods.

Amolins et al. (2007) presented the different image fusion techniques using wavelet transform. When a PAN image is fused with MS imagery, the desired result is an image with the spatial resolution and quality of the PAN imagery, and the spectral resolution and quality of the MS imagery. Standard image fusion methods inject spatial detail into the MS imagery. In their work, an overview of image fusion technique is given, and the results from a number of wavelet-based image fusion methods are compared. It has been found that, wavelet-based methods perform better than the standard methods.

Wan-qiang & Chun-sheng (2008) focused on image fusion between MS images and PAN images using a wavelet analysis method. A new weighting technique is developed based on wavelet transformation for the fusion of a high spatial resolution and a low-resolution, MS images. This method improves a standard wavelet merger for merging the lower frequency components of MS image and PAN image by means of local deviation rules with weighting average. The fused image is reconstructed by an inverse wavelet transform. Also, a MS image fusion algorithm was proposed based on wavelet transform characteristic of human vision system. A wavelet transformation of each source image is performed. Then, a new fusion was presented based on human vision system corresponding high (low) frequency components divided into several blocks, and contrast error of every block is calculated, an adaptive threshold selection is proposed to decide which should be used to construct the new high (low) frequency components. Finally, the fused image is obtained by taking inverse wavelet transform.

Yang et al. (2008) proposed a spatial domain and frequency domain integrated approach to fuse the multifocus images. It composes of computing Sum-Modified-Laplacian (SML) for each focus image, SWT decomposition, image fusion and inverse SWT. Initially, two initial binary decision maps are created by setting two thresholds to the SML difference between two focus images. Secondly, two different focus images are decomposed using SWT, then in the SWT domain, the new SWT coefficients are acquired by adopting a simple fusion rule. Low-bands coefficients are integrated using the weighted average, and high-bands coefficients are integrated using choose max and the two SML maps. Finally, the fused image is obtained by performing an inverse SWT transform.

Yang et al. (2014) introduced DWT based fusion technique with a novel coefficient's selection algorithm. After the source images are decomposed by DWT, two different window-based fusion rules are separately employed to combine the low frequency and high frequency coefficients. In this method, the coefficients in the low frequency sub-bands with maximum sharpness focus measure are selected as coefficients of the fused image, and a maximum neighboring energy based fusion scheme was proposed to select high frequency sub-bands coefficients. The performance assessment of the proposed method was conducted in both synthetic and real multi-focus images.

Table 2.1 Comparison of Wavelet based Image Fusion

Name of the Authors with Year	Title of the Paper	Contributions
Shi et al. (2005)	Wavelet-based image fusion and quality assessment	A multi-band wavelet-based method was introduced for fusing the images.
Pradhan et al. (2006)	Estimation of the number of decomposition levels for a wavelet-based multiresolution multisensor image fusion	Wavelet-based scheme for the fusion of MS and PAN images due to its ability to preserve the spectral fidelity of the MS image while improving its spatialquality.
Zheng et al. (2007)	A new metric based on spatial frequency and its application to DWT based fusion algorithm	The a DWT method incorporates PCA and morphological processing into DWT for fusion purpose.
Amolins et al. (2007)	Wavelet based image fusion techniques-An introduction, review and comparison	An overview of image fusion techniques is given and the results from a number of wavelet-based image fusion methods are compared.
Wan-qiang & Chun-sheng (2008)	Multi-spectral image fusion method based on wavelet transformation	A new fusion was presented based on human vision system corresponding high (low) frequency components divided into several blocks, and contrasterror of every block is calculated, an adaptive threshold selection is proposed to decide which should be used to construct the new high (low) frequency components.

Yang et al. (2008)	A spatial domain and frequency domain integrated approach to fusion multifocus images	Multifocus images are decomposed using SWT. Low, high frequency bands coefficients are integrated using the weighted average, choose max and the two SML maps.
Yang et al. (2014)	Multi-focus image fusion using an effective discrete wavelet transform based algorithm	The source images are decomposed by DWT and two different window-based fusion rules are separately employed to combine the low frequency and high frequency coefficients.

2.3 Survey On Pyramid Based Image Fusion

Image pyramids have been initially described for a multiresolution image analysis and as a model for the binocular fusion in human vision. An image pyramid is a sequence of images where each image is constructed by low pass filtering and subsampling from its predecessor. Due to subsampling, the image size is halved in both spatial directions at each level of the decomposition process thus leading to a multiresolution signal representation.

Toet (1989) presented in which iterative morphological filters of many scales but identical shape serve as basic functions. Structural pattern decomposition is achieved by subtracting successive layers in the multiresolution representation. The representation differs from established techniques in that the code elements have a well-defined location and size. The resulting image description provides a useful basis for multiresolution shape analysis.

In Toet et al. (1989), integration of images from different sensing modalities can produce information that cannot be obtained by viewing the sensor outputs separately and consecutively. The author introduced a hierarchical image merging scheme based on multiresolution contrast decomposition (the ratio of low-pass pyramid). The composite images produced by this scheme preserve those details from the input images that are most relevant to visual perception. The method was tested by merging parallel registered thermal and visual images. The results show that the fused images present a more detailed representation of the depicted scene. Detection, recognition and search tasks may therefore benefit from this new image representation. Cui et al. (1998) presented a fusion technique using contrast pyramid.

Petrovic & Xydeas (2004) proposed a system which uses a "fuse- then-decompose" technique realized through fusion/decomposition system architecture. Information fusion is performed on a multiresolution gradient map representation of image. At each resolution, input images are represented as gradient maps and combined to produce new, fused gradient maps. Fused gradient map signals are processed, using gradient filters derived from high- pass quadrature mirror filters to yield a fused multiresolution pyramid representation. The fused output image is obtained by applying a reconstruction process on the fused pyramid. This new gradient fusion significantly reduces the amount of distortion artifacts and the loss of contrast information usually observed in fused images obtained from conventional multiresolution fusion schemes. The fusion in the gradient map domain significantly improved the reliability of the feature selection and information fusion processes.

Table 2.2 Comparison of Pyramid based Image Fusion

Name of the Authors with Year	**Title of the paper**	**Contributions**
Toet (1989)	A morphological pyramidal image decomposition	Iterative morphological filters of many scales are used for image fusion.
Toet et al. (1989)	Merging thermal and visual images by a contrast pyramid	A hierarchical image merging scheme was introduced based on multiresolution contrast decomposition (ratio of low- pass pyramid).

Cui et al. (1998)	Image fusion with high-speed DSP	A contrast pyramid is used for image fusion.
Petrovic & Xydeas (2004)	Gradient-based multiresolution image fusion	Information fusion is performed on a multiresolution gradient map representation domain of image signal information

2.4 Survey On Other Image Fusion Techniques

In Srinivasa Rao et al. (2012), image fusion using fuzzy and neuro fuzzy logic approaches utilized to fuse images from different sensors, in order to enhance visualization. They explored the comparison between fuzzy based image fusion and neuro fuzzy fusion technique along with quality evaluation indices for image fusion like Mutual Information (MI) measure, fusion factor, image quality index, fusion symmetry, fusion index, root mean square error, Peak Signal to Noise Ratio (PSNR), entropy, correlation coefficient and Spatial Frequency (SF).

Li et al. (2013) proposed a fast and effective image fusion method for creating a highly informative fused image through merging multiple images. The proposed method is based on a two-scale decomposition of an image into a base layer containing large scale variations in intensity, and a detail layer capturing small scale details. A novel guided filtering-based weighted average technique was proposed to make full use of spatial consistency for fusion of the base and detail layers. This method can be used for fusion of multispectral, multi focus, multimodal, and multi exposure images.

Tank et al. (2013) represented the image fusion using wavelet transform and second generation curvelet transform. Since wavelet transform do not represent the edges and singularities well, the second generation curvelet transform is performed along with the wavelet transform and the image fusion is done. Finally, the proposed algorithm is applied to multifocus image fusion and complementary image fusion. Miles et al. (2013) presented spine image fusion via graph cuts. They used MRI and CT images of spine for fusion purpose.

Himanshi et al. (2015) presented a combination of curvelet transform along with PCA and maximum selection rule as an improved fusion approach for MRI and CT-scan. Curvelet transform achieves a compact representation of edges and curved shapes in the image. This property of curvelet transform facilitates the retrieval of complementary information from medical images for precise and efficient clinical diagnosis. The proposed fusion approach involves image decomposition using curvelet transform followed by application of PCA for dimensionality reduction and the selection of maximum matrix to select only the relevant information in the images.

Singh et al. (2015) presented a new fusion scheme for the CT and MR medical images that utilizes both the features of the nonsubsampled shearlet transform (NSST) and spiking neural network. As a new image representation with the different features, the NSST is utilized to provide an effective representation of the image coefficients. Firstly, the source CT and MR images are decomposed by the NSST into several subimages. The regional energy is used to fuse the low frequency coefficients. High frequency coefficients are also fused using a pulse coupled neural network model that is used as a biologically inspired type neural network. It also retains the edges and detail information from the source images. Finally, the inverse NSST is used to produce the fused image.

Moin et al. (2016) presented a weighted PCA based approach for multimodal fusion in Contourlet domain. The sole aim of using contourlet transform is because of its adeptness to capture visual geometrical structures and anisotropy. Further, weighted PCA assists in reducing the dimensionality of the source images as well as helps in better selection of principal components. Maximum and minimum fusion rules are then applied to fuse the decomposed coefficients. Image quality assessment is carried out using standard fusion metrics quantitatively to assess the fused image both in terms of information content as well as quality of reconstruction.

Table 2.3 Comparison of Different Image Fusion Techniques

Name of the Authors with Year	Title of the Paper	Contributions
Srinivasa Rao et al.(2012)	Comparison of fuzzy and neuro fuzzy image fusion techniques and its applications	A fuzzy and neuro fuzzy logic approaches are used to fuse the images.
Li et al. (2013)	Image fusion with guided filtering	A novel guided filtering-based weighted average technique was proposed for image fusion.
Tank et al. (2013)	Image fusion based on wavelet and curvelet transform	The image fusion has been done using wavelet transform and second generation curvelet transform.
Miles et al. (2013)	Spine image fusion via graph cuts	CT and MRI images of spine are fused using graph cuts method.
Himanshi et al. (2015)	Medical image fusion in curvelet domain employing PCA and maximum selection rule	A combination of curvelet transform along with PCA and maximum selection rule as an improved fusion approach for MRI and CT-scan is presented.
Singh et al. (2015)	Nonsubsampled shearlet based CT and MR medical image fusion using biologically inspired spiking neural network	Presented a new fusion scheme for the CT and MR medical images that utilizes both the features of the NSST and spikingneural network
Moin et al. (2016)	Weighted-PCA based multimodal medical image fusion in contourlet domain	Maximum and minimum fusion rules are applied to fuse the decomposed coefficients.

2.5 Survey On Wavelet Based Medical Image Fusion

Yu et al. (2001) proposed multi-modality medical image fusion which has important applications in medical image analysis and understanding. They developed multi-resolution method based on wavelet transform to fuse medical images from different modalities such as PET-MRI and CT-MRI. The different fusion results are evaluated when applying different selection rules and obtained optimum combination of fusion parameters.

Guihong et al. (2001) discussed multimodality medical image fusion using wavelet transform. A fusion rule is used for calculating the wavelet transformation modulus maxima of input images at different bandwidths and levels. To evaluate the fusion result, a metric based on Mutual Information (MI) is presented for measuring fusion effect.

Garg et al. (2005) implemented and analyzed a region level-based image fusion technique using wavelet transform. A segmentation algorithm was proposed for extracting the regions in an effective way for fusing the images. The proposed methodology considered regions as the basic feature for representing images and uses region properties for extracting the information from them. A segmentation algorithm is used for extracting the regions in an effective way for fusing the images. The fusion strategy uses multilevel decomposition of the images obtained using wavelet transform. By analyzing the images at multiple levels, the fusion method is able to extract finer details from them and in turn improves the quality of the fused image.

Li et al. (2006) proposed an algorithm based on Lifting Wavelet Transform (LWT) to fuse multi-modality medical images. The lifting scheme is used to construct the wavelets and has several unique advantages in comparison with conventional convolution-based wavelet transform. It allows for an in-place implementation of wavelet transform and reduces computation time and memory requirement greatly. In this fusion algorithm, LWT is employed to decompose and reconstruct images to realize the fast image fusion. A local feature-based fusion rule is used to improve fusion quality and extract all significant features from multi-source images. The fusion of registered medical CT/MRI, CT/SPECT, MRI/PET images is performed.

Wang et al. (2006) presented the application of wavelet transformation to multimodality medical image fusion which covered the selection of wavelet function, the use of wavelet based fusion algorithms for fusing CT and MRI, and the fusion image quality evaluation.

Licai et al. (2008) proposed medical image fusion using Wavelet Packet Transform (WPT) with self-adaptive operator. In this algorithm, the medical images are decomposed using WPT, and the wavelet coefficients are fused with self-adaptive operators. The results show that this algorithm is feasible and effective for the clinical applications.

Singh et al. (2009) proposed a fusion algorithm to combine pairs of multispectral MRI such as T1, T2 and proton density brain images. The proposed algorithm utilized different features of RWT; mutual information based non-linear registration and entropy information to improve performance. The result showed that the proposed fusion algorithm preserved both edge and component information.

Yong Yang et al. (2009) presented wavelet-based approach for fusing CT and MRI images and compared with the DWT, and pyramid-based methods. Yong Yang et al. (2010) introduced wavelet transform based medical image fusion. The proposed method was compared with pixel averaging, gradient pyramid and DWT.

In Soma Sekhar & Giri Prasad (2011), a novel approach of image fusion on MRI and CT images using wavelet transform was proposed. The wavelets used in image fusion are classified into three categories Orthogonal, Bi-orthogonal and a 'trous' wavelet.

Although these wavelets share some common properties, each wavelet has a unique image decompression and reconstruction characteristics that lead to different fusion results. Their approach combines region and pixel-based fusion. A wavelet transforms and PCA are integrated to get better fusion results. The fusion results are compared visually and statistically to show that wavelet integrated method improves the fusion result by reducing the ringing or aliasing effects.

Zaveri & Zaveri (2011) proposed a novel region-based image fusion technique based on DWT using high boost filtering. The proposed algorithm allowed to achieve an accurate segmentation for region-based fusion using graph based normalized cut algorithm. The resultant segmented image is used for extracting the regions from the input registered source images which are further processed to fuse different regions using different fusion rules. Proposed method is applied to various categories of multi-focus and multimodality images.

Shen et al. (2012) proposed a novel cross-scale fusion rule for multiscale-decomposition-based fusion of volumetric medical images taking into account both intra-scale and inter-scale consistencies. An optimal set of coefficients from the multiscale representations of the source images is determined by effective exploitation of neighborhood information.

Rana & Arora (2013) explored different medical image fusion methods and their comparison to find out which fusion method gives better results based on the performance parameters. The medical images of MRI and CT images are fused to form new image. The DWT, PCA and Fuzzy Logic techniques are utilized for fusing two images and results are compared. The fusion performance is evaluated on the basis of RMSE, PSNR and Entropy.

In Mantale & Gaikwad (2013), they proposed the RWT based algorithm for medical image fusion, and compared with the other DWT based methods. These methods are assessed on the basis of statistical measures such as entropy, mean and standard deviation.

James & Dasarathy (2014) proposed medical Image Fusion: A survey of the state of the art. In this work, the fusion of medical images proved to be useful for advancing the clinical reliability of using medical imaging for medical diagnostics and analysis.

Deepika & Mary Sinduja (2014) proposed fusion of CT and MRI images using Haar Transform (HT). In their work, the results are compared with PCA and Laplacian Pyramid Transform (LPT). Daljitn Kaur & Mann (2014) presented the work in medical image fusion using Gaussian filter, DWT and Curvelet Transform.

Singh & Khare (2014) proposed RDWT based fusion for multimodal medical images. The proposed method used maximum scheme for fusion of medical images. The effectiveness of fusion results is shown using edge strength, and mutual information fusion metrics. The qualitative and quantitative comparison of the proposed method with spatial domain fusion methods proved the superiority of the proposed fusion method.

Nandeesh & Meenakshi (2015) presented a comparative study of medical image fusion algorithms along with its performance analysis. The DWT, SWT, PCA and Curvelet Transform techniques are employed and its experimental results are evaluated and compared. Bhavana & Krishnappa (2015) proposed medical image fusion based on DWT for brain regions with different activity levels. The system showed around 80-90% more accurate results with reduced distortion and without losing any anatomical information in comparison with the existing techniques.

Bhateja et al. (2015) presented a comparative analysis and evaluation of multi-modal medical image fusion methodologies employing wavelet as a multi-resolution approach and ridgelet as a multi-scale approach. The current work tends to highlight upon the utility of these approaches according to the requirement of features in the fused image. The PCA based fusion algorithm has been employed in both ridgelet and wavelet domains for the purpose of minimization of redundancies. The outcome of this analysis highlights the trade-off between the retrieval of information content and the morphological details in the finally fused image in wavelet and ridgelet domains.

Guruprasad et al. (2015) proposed a hybrid fusion algorithm for multimodality medical images. It aims at gathering relevant, disparate and complementary data in one order to enhance the information apparent in the images, as well as to amplify the reliability of the interpretation. This leads to more accurate data and increased utility. In addition, it has been stated that combined data provides for robust operational performance such as increased confidence, reduced ambiguity, and improved reliability. This work introduced a pixel level based 'Hybrid Concept' by integrating the conventional and advance fusion methods to overcome their demerits and enhance the image processing qualities like PCA, DWT, Discrete Curvelet Transform (DCT) to form a DWT-PCA, DCT-PCA, and proposing one DWT- DCT-PCA algorithm.

Mazaheri et al. (2015) presented a fusion method which particularly intends to increase the segment-ability of echocardiography features such as endocardial and improving the image contrast. In addition, it tries to expand the field of view, decreasing impact of noise and artifacts and enhancing the signal to noise ratio of the echo images. The proposed algorithm weights the image information regarding an integration feature between all the overlapping images, by using a combination of PCA and DWT. For evaluation, a comparison has been done between results of some well-known techniques and the proposed method. Also, different metrics are implemented to evaluate the performance of proposed algorithm. It has been concluded that the presented pixel-based method based on the integration of PCA and DWT has the best result for the segment-ability of cardiac ultrasound images and better performance in all metrics.

Agarwal & Bedi (2015) proposed a hybrid technique using curvelet and wavelet transform used in medical diagnosis. In this technique, the image is segmented into bands using wavelet transform, the segmented image is then fused into sub bands using curvelet transform which breaks the bands into overlapping tiles and efficiently converting the curves in images using straight lines. These tiles are integrated together using inverse wavelet transform to produce a highly informative fused image. Wavelet based fusion extracts spatial details from high resolution bands but its limitation lies in the fusion ofcurved shapes. Therefore, for better information and higher resolution on curved shapes we are blending wavelet transform with curvelet transform as we know that curvelet transform deals effectively with curved areas, corners and profiles. These two fusion techniques are extracted and then fused, implementing hybrid image fusion algorithms. Findings show that fused images have minimum errors and present better-quality results.

Table 2.4 Comparison of Wavelet based Medical Image Fusion

Name of the Authors with Year	Title of the Paper	Contributions
Yu et al.(2001)	Multi-modality medical image fusion based on wavelet analysis and quality evaluation	A wavelet based approach is to fuse medical images from different modalities such as PET-MRI and CT-MRI.
Guihong et al.(2001)	Medical image fusion by wavelet transform modulus maxima	A fusion rule is used for calculating the wavelet transformation modulus maxima of input images.
Garg et al.(2005)	Multilevel medical image fusion using segmented image by level set evolution with region competition	A region level based image fusion technique using wavelet transform is used. A segmentation algorithm is used for extracting the regions for fusing the images.
Li et al.(2006)	A novel approach to fast medical image fusion based on lifting wavelet transform	LWT is applied to fuse multi-modality medical images. A local feature-based fusion rule is used to improve fusion quality and extract all significant features from multi- source images.
Wang et al.(2006)	The application of wavelet transform to multi-modality medical image fusion	A wavelet based fusion algorithm is used for fusing CTand MRI images.

Licai et al.(2008)	Medical image fusion based on wavelet packet transform and self-adaptive operator	The medical images are decomposed using WPT, and the wavelet coefficients are fused with self-adaptiveoperators.
Singh et al.(2009)	Multimodal medical image fusion using redundant discrete wavelet transform	A fusion algorithm combines pairs of multispectral MRI such as T1, T2 and proton density brain images.
Yang et al.(2009)	Wavelet based approach for fusing computed tomography and magnetic resonanceimages	Wavelet based approach is used for fusing CT and MRI images. The low and high frequency coefficients are performed with the maximal absolute values, and a maximal local variance rule.
Yang et al.(2010)	Medical image fusion via an effective wavelet- based approach	In wavelet based approach, the coefficients in low-frequency band, high-frequency bands are selected with a visibility and variance based method.
Soma Sekhar &Giri Prasad (2011)	A novel approach of image fusion on MR and CT images using wavelet transforms	An image fusion on MRI and CT images using wavelet transform was proposed. A wavelet transform and PCA are integrated to get better fusion results.
Zaveri & Zaveri(2011)	A novel region based multimodality image fusion method	A novel region based image fusion technique based on DWT using high boost filtering was proposed to achieve an accurate segmentation for region based fusion.
Shen et al.(2012)	Cross-scale coefficient selection for volumetric medical image fusion	A novel cross-scale fusion rule is applied for multiscale-decomposition-based fusion of medical images taking into account both intrascale and interscale consistencies.

Rana & Arora(2013)	Comparative analysis of medical image fusion	The DWT, PCA and Fuzzy Logic techniques are utilized for fusing two images. A different medical image fusion methods are compared to find out which fusion method gives better results based on the performance parameters.
Mantale & Gaikwad (2013)	Image fusion of brain images using redundant discrete wavelet transform	The RWT based algorithm is proposed for medical image fusion.
James & Dasarathy (2014)	Medical image fusion: a survey of state of the art	The fusion of medical images proved to be useful for advancing the clinical reliability of using medical imaging for medical diagnostics and analysis.
Deepika & MarySinduja (2014)	Performance analysis of image fusion algorithms using Haar wavelet	CT and MRI images are fused using Haar Transform.
Daljitn Kaur &Mann (2014)	Medical image fusionusing gaussian filter, wavelet transform and curvelet transform filtering	Medical image fusion has been done using Gaussian filter, Wavelet Transform (WT) and Curvelet Transform.
Singh & Khare(2014)	Redundant discrete wavelet transform based medical image fusion	RWT based image fusion was proposed using a maximum selection scheme for fusion ofmedical images.
Nandeesh & Meenakshi (2015)	Image fusion algorithms for medical images-A comparison	Comparative study of medical image fusion algorithms has been done along with its performanceanalysis.

Bhavana & Krishnappa(2015)	Multi-modality medical image fusion using discrete wavelet transform	Proposed medical image fusion based on DWT for brain regions with different activity levels.
Bhateja et. al(2015)	Medical image fusion in wavelet and ridgelet domains: A comparative evaluation	Presented a comparative analysis and evaluation of multi-modal medical image fusion methodologies employing wavelet as a multi-resolution approach and ridgelet as a multi-scale approach.
Guruprasad etal. (2015)	Fusion of CT and PET medical images using hybrid algorithm DWT-DCT-PCA	Proposed a hybrid fusion algorithmfor multimodality medical images using DWT-DCT- PCA algorithm.
Mazaheri et al.(2015)	Hybrid pixel-based method for cardiac ultrasound fusion based on integration of PCA and DWT	A fusion method which intends to increase the segmentability of echocardiography features such as endocardial and improving the image contrast is proposed.
Agarwal & Bedi (2015)	Implementation of hybrid image fusion technique for feature enhancement in medical diagnosis	Proposed a hybrid technique using curvelet and wavelet transformused in medical diagnosis

2.6 Survey On NSCT Based Image Fusion

Qu et al. (2008) proposed image fusion algorithm based on spatial frequency-motivated PCNN in NSCT Domain. NSCT is associated with PCNN and employed in image fusion to make full use of the characteristics of them. Spatial frequency in NSCT domain is input to motivate PCNN and coefficients in NSCT domain with large firing times are selected as coefficients of the fused image. Similar studies were conducted by Das & Kundu (2011), Yazdi & Ghasrodashti (2012), Wang et al. (2013), Wang et al.

(2014), Jianhui et al. (2015).

Li & Wang (2011) developed the biological image fusion using variable-weight fusion rule based on NSCT. The intensity components of original images are combined in the multiscaled space and the fused image is obtained in the Generalized HIS (GIHS) frame.

Chai et al. (2012) proposed an efficient multifocus image fusion approach based on local features contrast of multiscale products in the NSCT domain. To improve the quality of the fused image, novel different local features contrast measurements, which are proved to be more suitable for human vision system and can extract more useful detail information from source images and inject them into the fused image, are developed and used to select coefficients from the clear parts of subimages to compose coefficients of fused images. Experimental results demonstrated that the proposed method performs very well in fusion both noisy and noise-free multifocus images, and outperforms conventional methods in terms of both visual quality and objective evaluation criteria.

Das & Kundu (2012) proposed NSCT based multimodal medical image fusion using PCNN and modified spatial frequency. Liu (2012) introduced the NSCT based image fusion by considering human visual system and characteristics of images for PAN high resolution image and MS image.

Bhatnagar et al. (2013) introduced a NSCT based multimodal medical image fusion. In their work, a novel fusion framework was proposed for multimodal medical images based on NSCT. The source medical images are first transformed by NSCT followed by combining low and high frequency components. Two different fusion rules based on phase congruency and directive contrast are used to fuse low and high frequency coefficients. Finally, the fused image is constructed by the Inverse NSCT (INSCT) with all composite coefficients. The proposed framework is carried out by the three clinical examples of persons affected with Alzheimer, subacute stroke and recurrent tumor. This work enhanced the details of the fused image, and improved the visual effect with much less information distortion.

In Yong Yang et al. (2014), a novel NSCT based method for multimodal medical image fusion is presented which is approximately shift invariant and can effectively suppress the pseudo-Gibbs phenomenon. Sravya et al. (2014) proposed the multifocus image fusion using NSCT. The characteristics of NSCT were analyzed along with Wavelet and Curvelet Transform for simulation experiments on multi-focus images.

Choi (2014) analyzed and compared the performance of fusion methods based on four different transforms: i) wavelet transform, ii) curvelet transform, iii) contourlet transform and iv) nonsubsampled contourlet transform. Fusion framework and scheme are explained in detail. Furthermore, eight different performance metrics are adopted to comparatively analyze the fusion results. The comparison results show that the nonsubsampled contourlet transform method performs better than the other three methods, both spatially and spectrally.

Amini et al. (2014) proposed MRI-PET image Fusion based on NSCT. They fused MRI and PET images for the purpose of adding structural information from MRI to functional information of PET images.

Bhatnagar et al. (2015) presented NSCT based medical image fusion. Medical image fusion plays an important role in clinical applications such as image-guided surgery, image-guided radiotherapy, noninvasive diagnosis, and treatment planning. They proposed a novel framework for spatially registered multimodal medical image fusion, which is primarily based on the NSCT. This method decomposes the source medical images into low and high frequency bands in NSCT domain. The low-frequency components are fused using an activity measure based on the normalized Shannon entropy, which essentially selects low-frequency components from the focused regions with high degree of clearness. In contrast, high-frequency components are fused using the directive contrast, which essentially collected all the informative textures from the source. Integrating these fusion rules, more spatial feature and functional information are preserved and transferred into the fused images. The performance of the proposed framework was illustrated using four groups of human brain and two clinical bone images from different sources.

Bhateja et al. (2015) presented a two-stage multimodal fusion framework using the cascaded combination of SWT and NSCT domains for images acquired using two distinct medical imaging sensor modalities. The major advantage of using a cascaded combination of SWT and NSCT is to improve upon the shift variance, directionality, and phase information in the finally fused image. The first stage employs a principal component analysis algorithm in SWT domain to minimize the redundancy. Maximum fusion rule is then applied in NSCT domain at second stage to enhance the contrast of the diagnostic features. A quantitative analysis of fused images is carried out using fusion metrics. The fusion responses of the proposed approach are also compared with other state-of-the-art fusion approaches; depicting the superiority of the obtained fusion results.

Bangar & Chaudhari (2016) presented the NSCT based spine image fusion which fuses CT images and MRI images of spine into a single image containing both information of CT and MRI modalities.

Guo, Y & Huang, Y (2016) proposed a medical image fusion algorithm based on multi-channel PCNN in NSCT Domain. The proposed method exploits the advantage of the multi-scale and multiple directions of NSCT. NSCT transform is applied to get the low- frequency and high- frequency sub-bands of the two source medical images. Low-frequency coefficients are fused by using the average rules, while high-frequency coefficients are fused by inputting to the m-PCNN.

Table 2.5 Comparison of NSCT based Image Fusion

Name of the Authors with Year	Title of the Paper	Contributions
Qu et al. (2008)	Image fusion algorithm based on spatial frequency-motivated pulse coupled neural networks in nonsubsampled contourlet transform domain	Image fusion algorithm is based on spatial frequency-motivated PCNN in NSCT domain.
Li & Wang (2011)	Biological image fusion using a NSCT based variable-weight method	The biological image fusion is based on variable-weight fusionrule based on NSCT.
Chai et al. (2012)	Multifocus image fusion based on features contrast of multiscale products in nonsubsampled contourlet transform domain	An efficient multifocus image fusion approach is based on local features contrast of multiscale products in NSCT domain.
Das & Kundu (2012)	NSCT-based multimodal medical image fusion using pulse-coupled neural network and modified spatial frequency	NSCT based multimodal medical image fusion is presented using PCNN and modified spatial frequency.
Liu (2012)	Image fusion method basedon non-subsampled contourlet transform	NSCT based image fusion is presented by considering human visual system and characteristics of images, for PAN high resolution image and MS image.
Bhatnagar et al. (2013)	Directive contrast based multimodal medical image fusion in NSCT domain	A novel fusion framework is based on NSCT for fusing medical images. Two different fusion rules based on phase congruency and directive contrast are used to fuse low and high frequency coefficients.

Yong Yang et al. (2014)	Log-Gabor energy based multimodal medical image fusion in NSCT domain	A novel NSCT based method for multimodal medical image fusion is presented, which is approximately shift invariant and can effectively suppress the pseudo-Gibbs phenomena.
Sravya et al. (2014)	Image fusion multi on focused using SCT images	The characteristics of NSCT were analyzed along with wavelet and curvelet transform for simulation experiments on multi-focus images.
Choi (2014)	Quality assessment of image fusion methods in transform domain	Analyzed and compared the performance of fusion methods based on four different transforms: i) wavelet transform, ii) curvelet transform, iii) contourlet transform and iv) nonsubsampled contourlet transform.
Amini et al. (2014)	MRI-PET image fusion based on NSCT transform using local energy and local variance fusion rules	An image fusion is based on NSCT. MRI and PET images are fused for the purpose of adding structural information from MRI to functional information of PET images.
Bhatnagar et al. (2015)	A new contrast based multimodal medical image fusion framework	In NSCT based image fusion, the low and high frequency components are fused using an activity measure based on the normalized Shannon entropy and the directive contrast.
Bhateja et al. (2015)	Multimodal medical image sensor fusion framework using cascade of wavelet and contourlet transform domains	Presented a two-stage multimodal fusion framework using the cascaded combination of SWT and NSCT domains for images acquired using two distinct medical imaging sensormodalities.

Bangar & Chaudhari (2016)	NSCT based spine image fusion	NSCT based spine image fusion is presented which fuses CT images and MRI images of spine into a single image containing both information of CT and MRI modalities.
Guo, Y & Huang, Y (2016)	A medical image fusion algorithm based on multi-channel PCNN in NSCT Domain	NSCT is applied to get the low and high- frequency sub-bands of the two source medical images. Low-frequency coefficients are fused by using the average rules, while high-frequency coefficients are fused by inputting to the m-PCNN.

2.7 Comparison Of Images

The different image modality images X-ray, CT, MRI, PET and SPECT images are described in this section. These images provide limited information. Hence, imaging data is to be collected from the same patient using different modalities to undergo joint analysis. Image fusion aims to give single fused image which contains more accurate and reliable information. Such a fused image helps radiologists in visual diagnosis and further treatment.

Table 2.6 Comparison of Different Image Modalities

Image Modalities	Description of Image Modalities
X-ray	**X-rays** are useful in detecting abnormalities within the body. They are a painless, non-invasive way to help diagnose problems such as broken bones, tumors, dental decay, and the presence of foreign bodies. (http://www. healthofchildren.com).

CT	**CT** scans can be performed on every region of the body for a variety of reasons (e.g., diagnostic, treatment planning, interventional, or screening). CT image can provide dense structures like bones and implants with less distortion, but it cannot detect physiological changes (Yang at el. 2010).
MRI	**MRI** is a non-invasive imaging technology used for disease detection, diagnosis, and treatment monitoring. It can provide normal and pathological soft tissues information, but it cannot support the bones information (Yang et al. 2010).
PET	**PET** is a nuclear medicine, functional imaging technique that is used to observe metabolic processes in the body. PET can be used to provide better information on blood flow and flood activity with low spatial resolution (Bhatnagar et al. 2013). One of the disadvantages of PET scanners is their operating cost.
SPECT	**SPECT** scan is used to analyze the function of some of internal organs. A SPECT scan is a type of nuclear imaging test. SPECT scan produces images that show how your organs work. For instance, a SPECT scan can show how blood flows to your heart or what areas of your brain are more active or less active (http: //www. mayoclinic.org).

2.8 Research Gap

The image fusion problem has been broadly studied by researchers in the area of medical imaging, remote sensing, satellite and surveillance, etc. Many image fusion techniques have been framed using wavelet transform and NSCT. In the last few years, researchers have started paying attention to the medical image fusion using wavelet transform and NSCT based image fusion techniques. With the help of several image processing algorithms, it is possible to fuse the medical images. Fusion of medical images should be taken carefully as the whole diagnosis process depends on it. Medical images should be of high resolution with maximum possible details. The main challenge in medical image fusion is to produce efficient algorithm for fusing the images. The performance of image fusion can be improved by extracting more detail information from the input images.

2.9 Summary

This chapter summarized the literature survey on image fusion techniques. Various techniques have been used for fusing the images to create a single enhanced image which is more suitable for the purpose of human visual perception, object detection and target recognition. Image fusion has been done in pyramid based, wavelet based and NSCT based techniques. Although selection of fusion technique is problem dependent, spatial domain approach provides high spatial resolution. But, it has image blurring problem. The different pyramid schemes have been used in image fusion techniques which has the problem of blocking artifacts. The wavelet transform and NSCT based image fusion techniques provide a high quality spatial and spectral content of the images. Still, there is a requirement for efficient image fusion techniques. To overcome these problems, a novel image fusion technique is proposed in the next chapter.

CHAPTER-3

METHODOLOGIES

Fusion imaging is one of the most precise, contemporary, and useful diagnostic techniques in medical imaging today. It is useful in-patient care by compressing the time between diagnosis and treatment. Image fusion is the process by which two or more images are combined into a single image retaining the important features from each of the original images. Image fusion gives the high-quality fused image with spatial and spectral information.

Now-a-days, medical image fusion has become a new promising research field. For diagnosing the diseases, MRI and CT images are very important. MRI image provides better information about soft tissue and CT image provides detail information about dense structure such as bones. These two images provide complementary information. The main purpose of medical image fusion is to obtain a high resolution image with more details for the diagnosis purpose. Hence, if two images of the same organ are fused, then the fused image contains much information for diagnosis of that organ.

Many researchers have performed a lot of work on the fusion of medical images using DWT. The image fusion method based on DWT has good spatial information. It preserves different frequency information and allows good localization both in time and spatial frequency domain. However, one of the major drawbacks of DWT is that the transformation does not provide shift invariance. This causes a major change in the wavelet coefficients of the image even for minor shifts in the input image. In medical imaging, it is important to know and preserve the exact location of these information; but shift variance may lead to inaccuracies. For example, in medical image fusion, preservation edge information is needed, but DWT based fusion may produce specularities along the edges (Singh et al. 2009).

In order to overcome the shift variance problem of DWT, image fusion method using SWT which is shift invariant is proposed in this research work for medical applications (Fowler 2005). SWT has been applied in different signal processing applications but it is not well researched in the field of medical image fusion. For fusion of medical images, two different fusion rules that are proposed for detailed bands are canny operator and morphological processing. The low frequency bands are fused by maximum selection rule. The experimental results on four pairs of medical images are compared in terms of mean, standard deviation, spatial frequency, average gradient and $Q^{AB/F}$ as performance parameters. Experimental results show that the proposed methods improve the quality of fused medical images compared with other conventional approaches.

3.1 Discrete Wavelet Transform

The wavelet transform is a mathematical tool which was first developed by Mallat (2006). It can be applied to image processing applications. It is used to decompose two dimensional (2D) signals into different resolution levels for multiresolution analysis.

Wavelet transform are used in many areas such as,

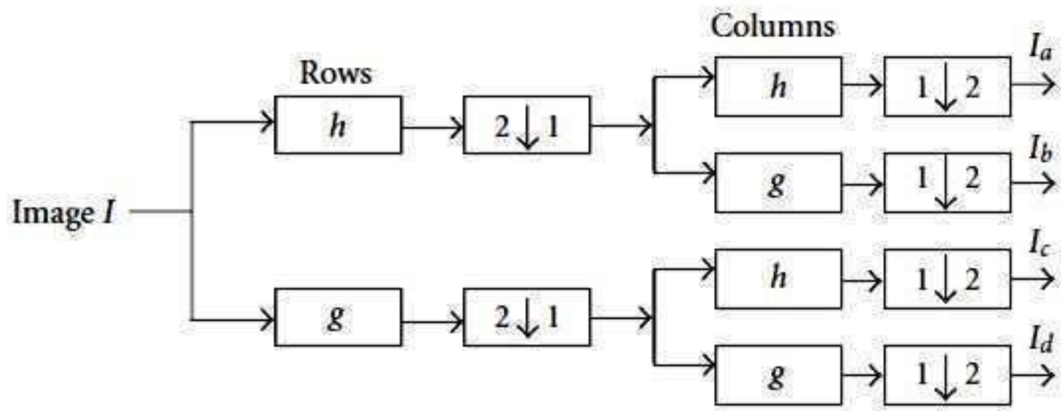
- Data compression
- Texture analysis
- Feature detection
- Image fusion.

The wavelet transforms provide a framework in which a signal is decomposed, with each level corresponding to a coarser resolution or lower-frequency band and higher-frequency bands. There are two main groups of transforms,

- Continuous Wavelet Transform

- Discrete Wavelet Transform

The DWT applies a two-channel filter bank iteratively to the low pass band. The wavelet representation consists of low-pass band at the lowest resolution and the high pass bands obtained at each step. This transform is non redundant and invertible. The DWT provides a multiresolution analysis of an image. The idea of one dimensional (1D) DWT is to represent the signal as a superposition of wavelets. Assume that a discrete signal is represented by *f (t)*. Image respectively as shown in Figure 3.1. Figure 3.2 shows the structures of 2D DWT with 3 decomposition levels.



(Source: Yang et al. 2010)

Figure 3.1 One Level of 2D DWT Multiresolution Image Decomposition

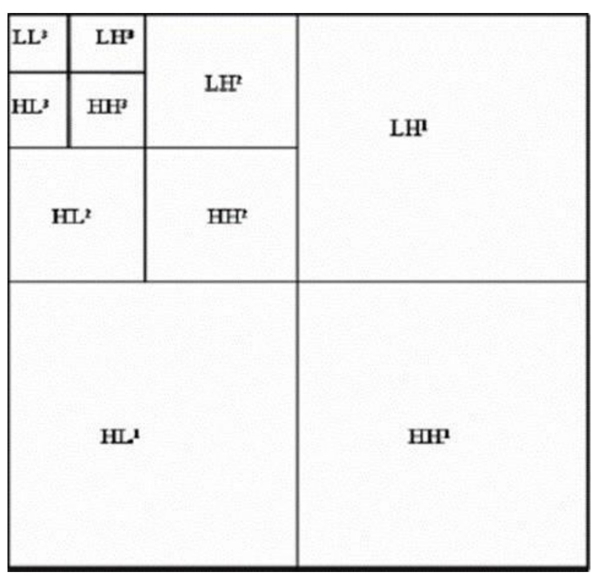
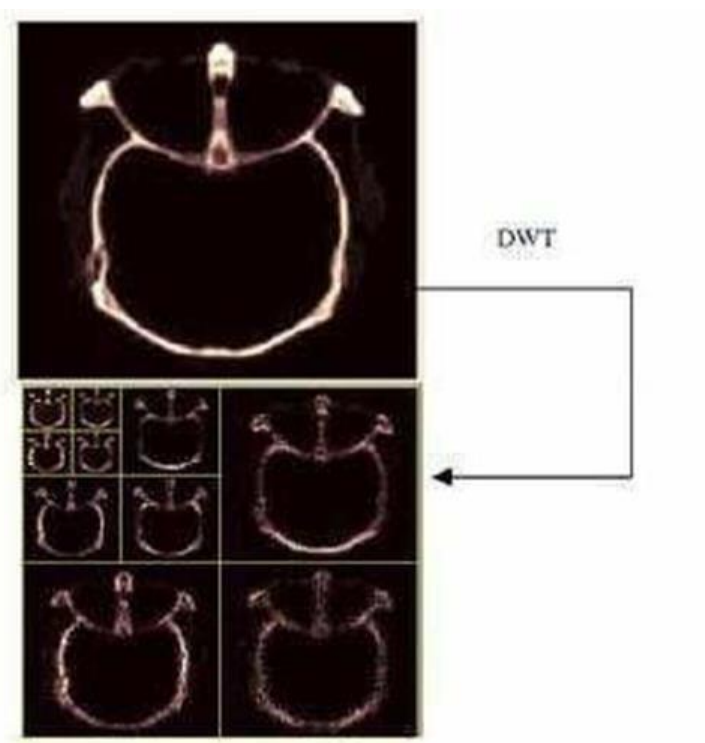


Figure 3.2 Structures of 2D DWT with 3 Decomposition Levels

Actually, wavelet transform can be taken as one special type of pyramid decompositions. After one level of decomposition, there will be four frequency bands, namely Low-Low (LL), Low-High (LH), High-Low (HL) and High-High (HH). The next level decomposition is just applied to the LL band of the current decomposition stage, which forms a recursive decomposition procedure.

Thus, N-level decomposition will finally have 3N+1 different frequency bands, which include 3N high frequency bands and one LL frequency band. The 2D DWT will have a pyramid structure shown in the above Figure 3.2. The frequency bands in higher decomposition levels will have smaller size. The image decomposition result at level 3 is as shown in Figure 3.3.



(Source: Wang et al. 2010)

Figure 3.3 Image Wavelet Decomposition at Level 3

3.2 Image Fusion Based On Discrete Wavelet Transform

The scheme of image fusion is described in the Figure 3.4.

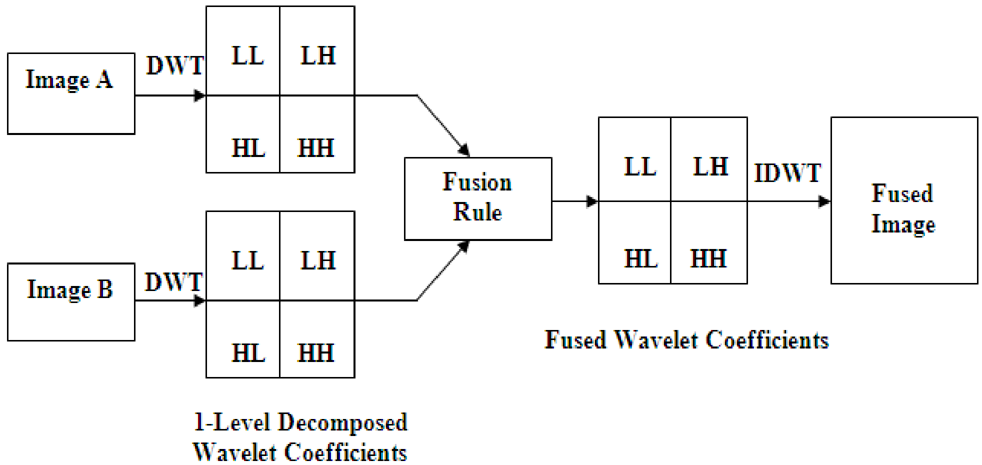


Figure 3.4 Scheme of Image Fusion Method based on DWT

Image fusion is a methodology concerned with the integration of multiple images, e.g. derived from different sensors, into a composite image that is more suitable for the purposes of human visual perception or computer- processing tasks. Since the essential goal of fusion is to preserve image featuresfrom the sources, a plausible approach is to transform the images into representations that decompose the images into relevant features such as edges, and perform fusion in this domain. A multiresolution representation facilitates this type of analysis because it decomposes an image into different scales while preserving locality in space.

In general, the basic idea of image fusion based on wavelet transform is to perform multiresolution decomposition on each source image. The coefficients of both the low-frequency and high-frequency bands are then performed with a certain fusion rule. The widely used fusion rule is maximum selection scheme. Maximum selection scheme just selects the largest absolute wavelet coefficient at each location from the transformed input images. Then, the fused image is obtained by performing the IDWT for the corresponding combined wavelet coefficients.

The following are the general steps which are followed in any image fusion methods:-

Step 1: The images to be fused must be registered to assure that the corresponding pixels are aligned.

Step 2: These images are decomposed into wavelet transformed images, respectively, based on wavelet transformation. The transformed images with K-level decomposition will include one low-frequency band (low-low band) and 3K level high-frequency bands (low-high bands, high-low bands, and high-high bands).

Step 3: The transform coefficients of different bands are performed with a certain fusion rule.

Step 4: The fused image is constructed by performing an inverse wavelet transform based on the combined transform coefficients obtained from Step 3.

Overview of NSCT

This proposes a new NSCT-based multimodal medical image fusion technique which utilizes NSCT coefficient's statistical features to fit the high frequency coefficients with lower distortion and maximum information transfer. The highest quantity of data is transmitted to the fused image from source images, taking into the consideration of statistical characteristics of images like angular consistency of low frequency sub band images and High frequency sub band image energies. To obtain an effective detection of corner features, this method suggested an angular consistency mechanism that derives all possible features from the LF sub-band images in different orientations. A Spatio- frequency energy filter is proposed here by which all possible dominant characteristics of an image can be obtained at distinct orientations in order to achieve orientation invariant fused image. Finally, a new fusion rule is derived to acquire fused high frequency and low frequency sub-bands. For the performance evaluation of the proposed strategy, various models of medical images are processed. The performance is both visually and numerically analyzed.

3.3 Laplacian Pyramid (LP)

The basic classifications of pyramids are: Gaussian pyramid and Laplacian Pyramid. In Gaussian pyramid the original image G_0 is repeatedly filtered and sub sampled to generate the sequence of reduced resolution images G_1 , G_2 etc. These comprise a set of low pass filtered copies of the original image in which the bandwidth decreases in one octave steps. A specific pyramid is determined by its particular decimation factor and approximation and interpolation filters. In the Laplacian pyramid, two operators, REDUCE and EXPAND are commonly used. The REDUCE operator performs a two- dimensional (2-D) low pass filtering followed by a sub-sampling by a factor of two in both directions. The EXPAND operator enlarges an image to twice the size in both 57 directions by up-sampling (i.e., insertion of zeros) and a low pass filtering. This filtering is followed by a multiplication by a factor of four, which is necessary to maintain the average intensity being reduced by the insertion of zeros. For an input image I , let its Gaussian pyramid at layer l be G_l , and its Laplacian pyramid at layer l be L_l , where l=0,1,2,…..d-1 and d is the total decomposition layers. The Laplacian pyramid was introduced by Burt and Adelson (1983). An important property of the Laplacian pyramid is that it is a complete image representation. The Gaussian and Laplacian pyramid can be defined as:

$$G_0 = I$$

$$G_1 = \text{REDUCE}[G_{l-1}]$$

$$L_1 = G_l - \text{EXPAND}[G_{l+1}]$$

3.4 Directional Filter Bank(DFB)

The directional filter bank (DFB) that can be maximally decimated while achieving perfect reconstruction. The DFB is efficiently implemented via an l-level binary tree decomposition that leads to2^l sub bands with wedge-shaped frequency partitioning as shown in Figure 3.1. The original construction of the DFB involves modulating the input image and using quincunx filters banks with diamond-shaped filters. To obtain the desired frequency partition, a complicated tree expanding rule has to be followed for finer directional sub bands.

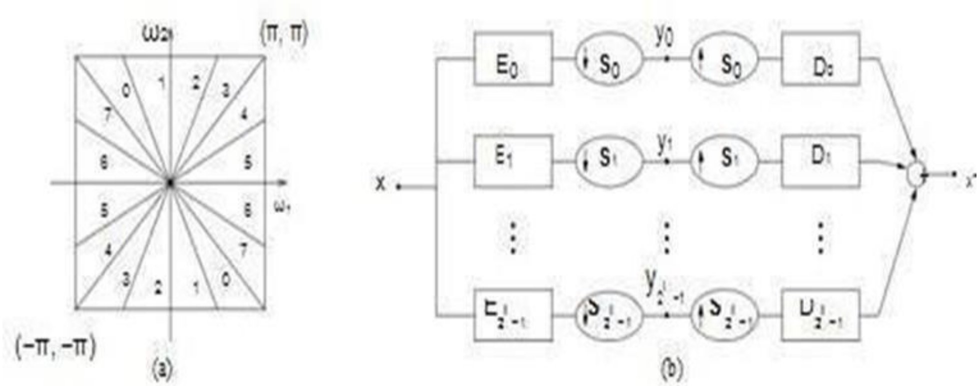


Figure 3.1.Directional filter bank. (a) Frequency partitioning where l= 3 and there are 2^3=8 real wedge-shaped frequency bands. (b) The multichannelview of

an **l**- level tree-structured directional filter ban

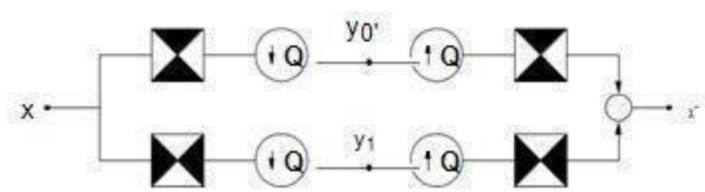


Figure3.2Two-dimensional spectrum partition using quincunx filter banks with fan filters. The black regions represent the ideal frequency supports of each filter. Q is a quincunx sampling matrix.

3.5 Non-Subsampled Pyramid (NSP)

The multiscale property of the NSCT is obtained from a shift-invariant filtering structure that achieves sub band decomposition similar to that of the Laplacian pyramid. This is achieved by using two-channel non-subsampled 2-D filter banks. Fig.3.3 and Fig.3.4 illustrates the non-subsampled pyramid(NSP) decomposition with J = 3stages and the Sub bands on the 2-D frequency plane respectively. Such expansion is conceptually similar to the one–dimensional(1-D) Non-Subsampled Wavelet Transform (NSWT) computed with the *à trous* algorithm[141] and has$J+1$ redundancy, where J denotes the number of decomposition stages. The ideal passband support of the low-pass filter at the jth stage is the region.

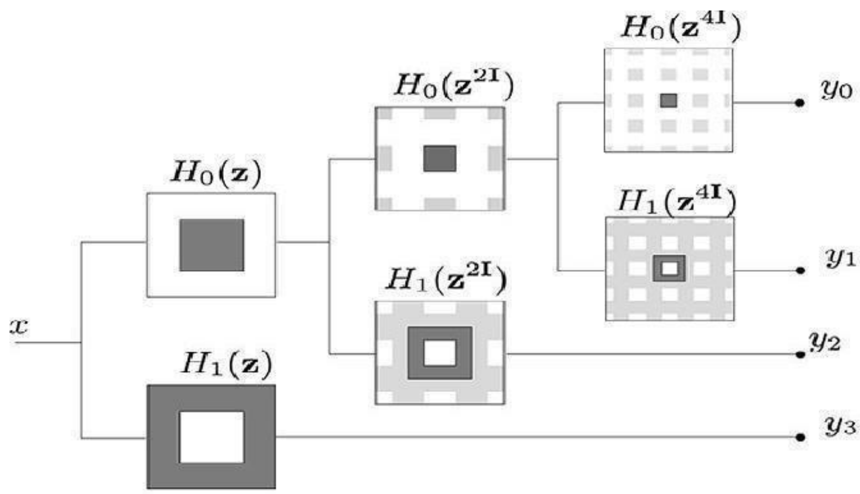


Figure3.3Three-stage pyramid decomposition. The lighter gray regions denote the aliasing caused by up-sampling

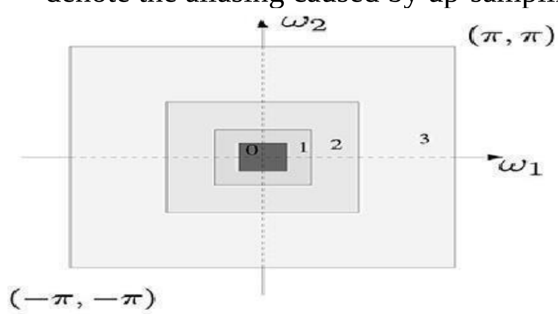


Figure3.4Subbands on the 2-D frequency plane

Accordingly, the ideal support of the equivalent high-pass filter is the complement of the region filters for subsequent stages that are obtained by up- sampling the filters of the first stage. This gives the multiscale property without the need for additional filter design. The proposed structure is thus different from the separable NSWT. In particular, one band- pass image is produced at each stage resulting in redundancy. By contrast, the NSWT produces three directional images at each stage, resulting in 3$J+1$redundancy. The 2-D pyramid proposed in [142] is obtained with a similar structure. Specifically, the NSFB of [142] is built from low-pass filter$H_O[z]$. One then sets $H_1[z]=1-H_O[z]$, and the corresponding synthesis filters $G_O[z]=G_1[z].=1$. A similar decomposition can be obtained by removing the down samplers and up samplers in the Laplacian pyramid and then up-sampling the filters accordingly. Those perfect reconstruction systems can be seen as a particular case of our more general structure. The advantage of our construction is that it is general and as a result, better filters can be obtained. In particular, in our design $G_O[z]$and$G_1[z]$ are low-pass and high-pass. Thus, they filter certain parts of the noise spectrum in the processed pyramid coefficients.

3.6 Non-subsampled Directional Filter Bank (NSDFB)

The directional filter bank of Bamberger and Smith [143] is constructed by combining critically-sampled two-channel fan filter banks and resampling operations. The result is a tree-structured filter bank that splits the 2-D frequency plane into directional wedges. A shift-invariant directional expansion is obtained with a non- subsampled DFB (NSDFB). The NSDFB is constructed by eliminating the down-samplers and up-samplers in the DFB [144]. This is done by switching off the down-samplers/ up-samplers in each two-channel filter bankin the DFB tree structure and up-sampling the filters accordingly. This results in a tree composed of two-channel NSFBs.

Figure.3.5 illustrates the fourchannel decomposition and Figure3.6 shows the corresponding frequency decomposition. Note that in the second level, the up-sampled fan filters $U_i(Z^Q)$, i = 0, 1 have checker-board frequency support, and when combined with the filters in the first level give the four directional frequency decomposition shown in Fig. 3.5. The synthesis filter bank is obtained similarly. Just like the critically sampled directional filter bank, all filter banks in the non-subsampled directional filter bank tree structure are obtained from a single NSFB with fan filters [see Figure.3.7]. Moreover, each filter bank in the NSDFB tree has the same computational complexity as that of the building-block NSFB.

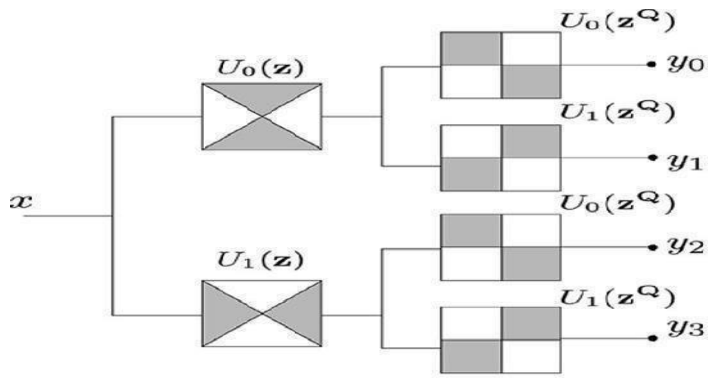


Figure3.5Filtering structure. The equivalent filter in each channel is given by $U^{Eq}_k(z) = U_i(z)U_j(Z^Q)$

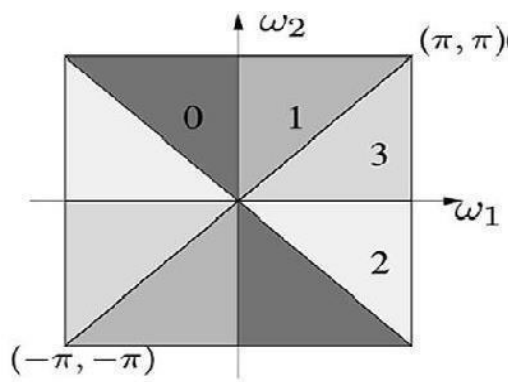


Figure3.6 Corresponding frequency decomposition

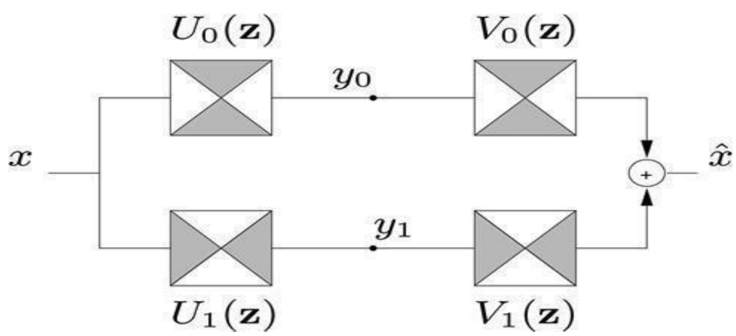


Figure3.7 Fan NSFB

3.7 Non-Subsampled Contourlet Transform (NSCT)

In this section, a concise overview of NSCT which decomposes the images into different sub-bands is outlined. Any transformation technique that decomposes an image should have a property of shift invariance. The absence of this property produces a side effect called Pseudo-Gibbs Phenomena. The image representation also considers, along with the shift invariance, the geometric pervasiveness that offers an efficient visual representation. In order to attain this, a new transformation called contourlet transformation (CT) [37] is established by using the directional filter bank (DFB)[2] in conjunction with the Laplacian Pyramid (LP)[1].It is actually a multi- scale and also the multidirectional transformation that decomposes the image in multiple scale and directions. In CT, the point singularities are captured by the Laplacian pyramid and the DFB links a linear framework between the obtained singular points. The image is originally decomposed via LP into bands of low frequency as well as high frequency, and the DFB further decomposes the bands of high frequency into directional sub-bands. The schematic decomposition of an image through CT is shown in figure.3.8.

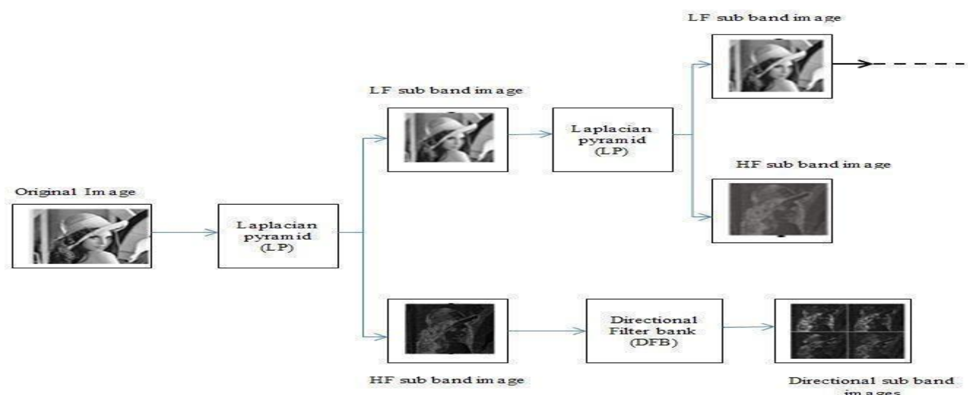


Figure 3.8. Schematic decomposition of image through CT

An image is decomposed into high and low frequency sub bands by means of CT, according to figure.3.8. It is decomposed into LF sub band image and HF sub band image upon an initial implementation of LP over actual image. Furthermore, the acquired LF sub band was processed again by LP to obtain fine LF sub bands that are more frequently coarser. DFB processes the HF sub band image to obtain directional sub bands of HF sub band image. CT is a hierarchical transformation, where LP hierarchically decomposes the LF sub band into finer frequency sub-bands. In the case of CT fusion in medical images, the source images A and B are decomposed into HF and LF sub band images. Further, the average rule is used for the fusion of LF bands and the maximum absolute rule is used for the fusion of HF bands. However, the redundancy of the pyramid filterbank in the CT is very small. The primary problem is therefore excessive overhead processing owing to the more redundant data, which is very crucial forcompression applications for medical images. Designing ideal filters for

contourlet transformation in particular, however, is a complicated job. Also the existence in the DFB and Laplacian pyramid of up-samplers and down-samplers makes the CT not shift-invariant.

The NSCT [121] is only developed on the basis of CT theory. In providing shift invariance, NSCT boosts directional selectivity and efficiently decreases the importance of pseudo-Gibbs events. The NSCT's process of decomposition is split into two stages, namely the Non-Sub Sampled Pyramids (NSP) and the Non- Sub Sampled Directional Filter Bank (NSDFB). The first decomposes in multiple scales and later decomposes the direction. At each level, the NSP divides the image into a HF sub band and a LF sub band. For a specified decomposition stage, the NSP produces *k+1* sub band image, comprising one image in a LF sub band image and the remaining *k* are HF sub band images. The NSDFB splits the HF sub-band image into directional sub band images. For a given level of decomposition *l*, 2^l directional sub band images will be obtained for a particular high frequency sub band image. After the low frequency component is decomposed iteratively by the same way, an image is finally decomposed into one low frequency sub image and a series of high frequency directional sub band images ($\sum^{k} 2^{Sj}$), where in lj denotes the number of decomposition directions at the j scale. Figure.3.9 represents the schematic of NSCT.

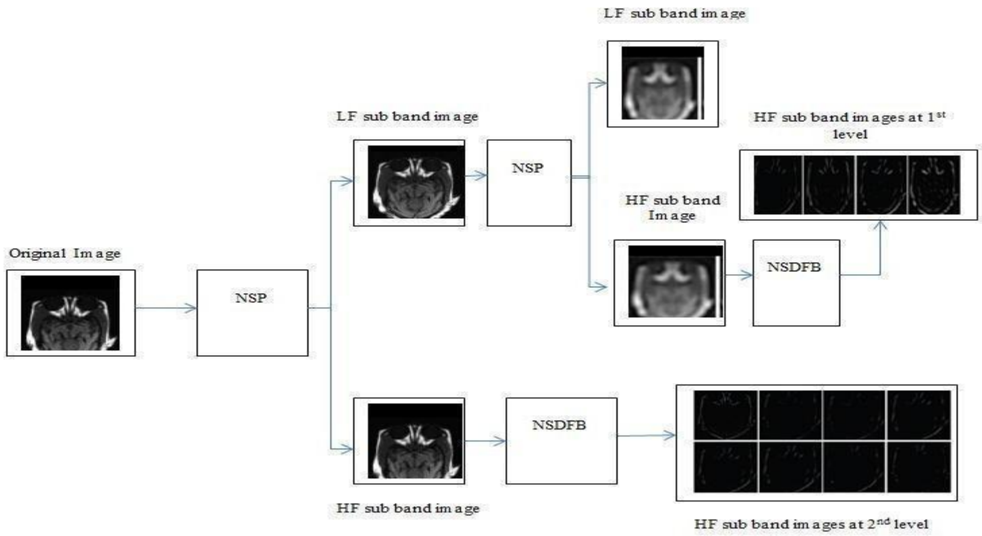


Figure3.9. Schematic decomposition of MRI image through NSCT

Thus, the NSDFB offers more accurate directional information to produce more accurate results through the bands obtained in multi-directional orientations. Thus, the NSCT ensures optimum frequency selectivity on the non- sampled operation aspect as well as a significant shift invariance property. Furthermore, the NSCT also decreases the impacts of misregistration over the outcomes acquired. The suggested model therefore regarded NSCT for MMIF.

CHAPTER-4
RESULTS AND DISCUSSIONS

4.1 Implementation

Here we have used a technique called Discrete Wavelet Transform is a mathematical tool for hierarchically decomposing an image. It decomposes a signal into a set of basis functions called wavelets. If the shape of the signal matches with wavelet, then higher value of transform is obtained. If the signal is not matches with wavelet then low transform value is obtained.

Firstly the input image is filtered along rows and then it is followed by filtering sub image along column. After Performing this Process it can offer the information in 4 ways as approximation(A), horizontal(H), vertical(V), and diagonal(D) coefficients. By this process we can only considering only $1/4^{th}$ sample of input image which is same as our input image.

The DWT decomposes the input sequence as low and high pass sub bands. Each sub band consists of half samples of the original input.

In DWT the input is analyzed with analysis filter bank succeeded by the operation called decimation. So here the input image is filtered along rows and decimated by two. Then it is followed by filtering sub image along column.

This process separates the input into sub bands as LL, LH, HL, HH respectively. Then perform the inverse discrete wavelet transform to the obtained image to get the fused image.

Now we have used another method called NSCT. NSCT is a shift invariant, multi-scale and multi-directional transform. Provides accurate analysis of multimodality images.

It is obtained by using the Non-subsampled Pyramid Filter Bank (NSP or NSPFB) and the Non-subsampled Directional Filter Bank (NSDFB). The source images are registered and decomposed into low and high freq. coefficients.

The low frequency coefficients fused and apply the avg. fusion rule and high frequency coefficients fused and apply max fusion rule. In each sub-band transform coefficients is same as the original image. Here quality is increased and provides better frequency selectivity. NSPFB used to divide images into low and high frequency components. NSDFB used to decompose high frequencies in each level of NSP. At each decomposition level of NSP, one low-frequency image and one high- frequency image can be produced. A pair of different multimodality source images is used for this experimental work. The traditional and proposed methods as well as proposed hybrid algorithms are used for the experimental work get the output image.

4.2 Result of reading images

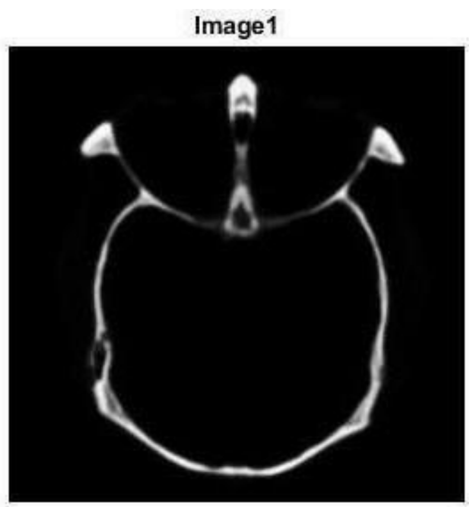


Figure 4.1: Image of CT scan

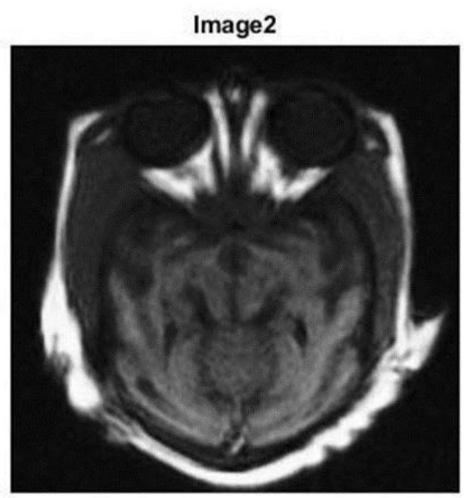


Figure 4.2: Image of MRI scan

```
clc;
clear all; close all;
%% Inputs fp=uigetfile('*.jpg;*.bmp');
I=imread(fp);
```

```
if size(I,3)>1
I = rgb2gray(I);
 end
figure; imshow(I);
title('Image1');
fp=uigetfile('*.jpg;*.bmp');
J=imread(fp);
if size(J,3)>1
J = rgb2gray(J);
end figure;
imshow(J); title('Image2');
```

4.3 Performance Characteristics

Entropy:

The average information of an image or the degree of randomness in the image. The entropy of a system as defined by Shannon gives a measure of uncertainty aboutthe images' actual structure. Shannon's function is based on the concept that the information gain from an event is inversely related to its probability of occurrence. Several authors have used Shannon's concept for image processing and pattern recognition problems.

```
ent=entropy(Final);
fprintf('ENTROPY=%f',ent);
```

Standard Deviation:

The tendency of the values in a data set to deviate from the average value. The SD is used to calculate distribution amount of intensities in fused image. The more results of this metric are bigger, the more the method is successful.

```
SDE=std(Finalg);
SDE=mean(SDE);
fprintf('\nStandard Deviation=%f',SDE);
```

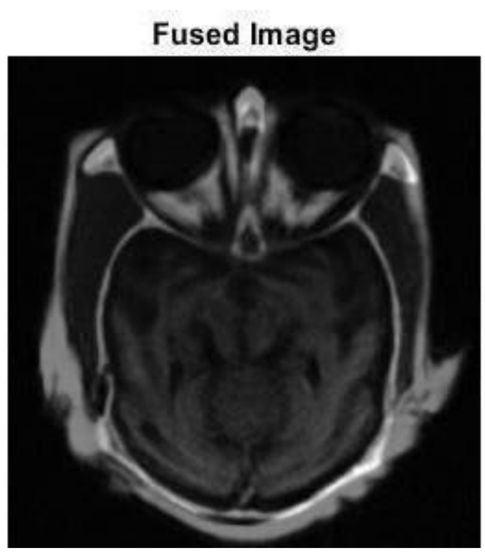
PSNR(Peak Signal to Noise Ratio):

It defines the ratio between the maximum possible signal power and the power of a noisy image.

More the PSNR, the quality of the image will be high

```
%psnr of the image I by taking Final image as reference
psnr1=psnr(I,Final);
fprintf('\nPSNR1=%f',psnr1);
%psnr of the image Final by taking second(ct) image as reference
psnr2=psnr(Final, J);
fprintf('\nPSNR2=%f',psnr2);
```

4.4 RESULT:



4.3 Fused Image

4.5 Performance Comparison

Table4.1: Performance Comparison

Parameters	Existing Method	Proposed Method
	Fused Image	Fused Image
PSNR1	30.26	31.753433
PSNR2	30.45	31.753433
Entropy	4.53	5.988268
Standard Deviation	0.13623	0.12663

From the above table we have concluded that we achieved higher values compared to our existing method. We achieved high PSNR and Entropy and low standard deviation so by this value we can prove that we have a more informative image which has greater visuality and less noisy image. Finally, From the performance measures the proposed algorithm yields better results and proposed work performs effectively over existing algorithms.

CHAPTER-5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

The proposed fusion system for multimodality medical images using the NSCT—DWT method gives better results. This method enhances the image quality with short processing time and the fused image to give much more details for better disease analysis. The NSCT-DWT has shown good results for the multimodality images. The proposed technique is superior for visual quality, precise analysis and accurate localization of the disease. From the performance measures the proposed algorithm yields better results and it can be applied in real time clinical applications. The comparison on the basis of various performance metrics, it also has been concluded that proposed work performs effectively over existing algorithms.

5.2 Future Scope

Image fusion means the combining of multiple images into a single image that has the most information contented without producing facts which can be missing in certain image. The design of image fusion in multi-focus cameras to combine data from various images of the related landscape in order to take the multi focused image.

The proposed work has been simulated in the MATLAB. The Image fusion using DWT and NSCT provides a future assistance where image is not only fused by gray image but also it can be applied for RGB image. The results indicate that the NSCT provides better performance than competing transform such as the curvelet transform. In future, new feature extraction technique along optimizations will be included in algorithms for better performance.

REFERENCES:

1. Agarwal, J & Bedi, SS 2015, „Implementation of hybrid image fusion technique for feature enhancement in medical diagnosis‟, Human- centric Computing and Information Sciences, vol. 5, no. 3, pp. 1-17.

2. Ali, FE, El-Dokany, IM, Saad, AA & Abd El-Samie, FE 2008, „Curvelet Fusion of MR and CT images‟, Progress In Electromagnetics Research C, vol. 3, pp. 215-224.

3. Amini, N, Fatemizadeh, E & Behnam, H 2014, „MRI-PET Image Fusion based on NSCT Transform using Local Energy and Local Variance Fusion Rules‟, Journal of Medical Engineering and Technology, vol. 38, no. 4, pp. 211-219.

4. Amolins, K, Zhang, Y & Dare, P 2007, „Wavelet based image Fusion Techniques-An introduction, review and comparison‟, ISPRS Journal of Photogrammetry and Remote Sensing, vol. 62, no. 4, pp. 249-263.

5. Bangar, D & Chaudhari, D 2016, „NSCT based Spine Image Fusion‟, International Journal of Industrial Electronics and Electrical Engineering, vol.4, issue.3, pp. 33-36.

6. Bhateja, V, Krishn, A, Himanshi & Sahu, A 2015, „Medical Image Fusion in Wavelet and Ridgelet Domain: A Comparative Evaluation‟, International Journals of Rough Sets and Data Analysis, vol.2, pp.78- 91.

7. Bhateja, V, Patel, H, Krishn, A, Sahu, A & Lay-Ekuakille, A 2015, „Multimodal Medical Image Sensor Fusion Framework using Cascade of Wavelet and Contourlet Transform Domains‟, IEEE Sensors Journal, vol. 15, no. 12, pp. 6783-6790.

8. Bhatnagar, G, Wu, QMJ & Liu, Z 2015, „A New Contrast based Multimodal

Medical Image Fusion Framework‟, Neurocomputing, vol. 157, pp. 143-152

9. Bhatnagar, G, Wu, QMJ & Liu, Z 2013, „Directive Contrast Based Multimodal Medical Image Fusion in NSCT Domain‟, IEEE Transactions on Multimedia, vol. 15, no. 5, pp. 1014-1024.

10. Bhavana, V & Krishnappa, HK 2015, „Multi-Modality Medical Image Fusion using Discrete Wavelet Transform‟, 4th International Conference on Eco-friendly Computing and Communication Systems, Procedia Computer Science, vol. 70, pp. 625-631.

11. Blum, R.S., Xue, Z. & Zhang, Z 2005, „Overview of image fusion. Multi-Sensor Image Fusion and Its Applications‟, Boca Raton, FL:CRC Press, pp.1-36.

12. Miles, B, Ayed, IB, Law, MWK, Garvin, G, Fenster, A & Li, S 2013, „Spine Image Fusion via Graph Cuts‟, IEEE Transactions on Bio- Medical Engineering, vol. 60, no. 7, pp. 1841-1850.

13. Chai, Y, Li, H & Zhang, X 2012, „Multifocus Image Fusion based on Features Contrast of Multiscale Products in Nonsubsampled Contourlet Transform Domain‟, Optik - International Journal for Light and Electron Optics, vol. 123, no. 7, pp. 569-581.

14. Chibani, Y & Houacine, A 1998, „Multiscale versus Multiresolution Analysis for Multisensor Image Fusion‟, 9th European Signal Processing Conference (EUSIPCO), pp.1-4.

15. Choi, Y, Sharifahmadian, E & Latifi, S 2014, „Quality Assessment of Image Fusion Methods in Transform Domain‟, International Journal on Information Theory, vol. 3, no. 1, pp.7-18.

16. Cui, Y, Pu, T, Ni, G, Zhong, Y & Li, X 1998, „Image fusion with high-speed

DSP‟ Proc. SPIE, Electronic Imaging and Multimedia Systems II, vol.3561 pp286-292.

17. Da Cunha, AL, Zhou, J & Do, MN 2006, „The Nonsubsampled Contourlet Transform: Theory, Design, and Applications‟, IEEE Transaction on Image Processing, vol.15, no.10, pp.3089-3101.

18. Daljit Kaur & Mann, PS 2014, „Medical Image Fusion Using Gaussian Filter, Wavelet Transform and Curvelet Transform Filtering‟, International Journal of Engineering Science and Advanced Technology, vol. 4, no. 3, pp. 252-256.

19. Daneshvar, S & Ghassemian, H 2010, „MRI and PET Image Fusion by combining IHS and Retina-inspired Models‟, Information Fusion, vol. 11, no. 2, pp.114-123.

20. Das, S & Kundu, MK 2011, „Ripplet based Multimodality Medical Image Fusion using Pulse-Coupled Neural Network and Modified Spatial Frequency, 2011 International Conference on Recent Trends in Information Systems, IEEE Press, pp.229-234.

21. Das, S & Kundu, MK 2012, „NSCT-Based Multimodal Medical Image Fusion using Pulse-Coupled Neural Network and Modified Spatial Frequency‟, Medical and Biological Engineering and Computing, vol. 50, pp.1105-1114.

22. Deepika, L & Mary Sindhuja, NM 2014, „Performance Analysis of Image Fusion Algorithms using HAAR Wavelet‟, International Journal of Computer Science and Mobile Computing, vol. 3, no. 1, pp.487- 494.

23. Dhawan, PA 2003, Medical Imaging Analysis. Hoboken (NJ): Wiley-Interscience Publication.

24. Ellmauthaler, A, Pagliari, CL & Da Silva, AB 2013, „Multiscale Image

Fusion Using the Undecimated Wavelet Transform With Spectral Factorization and Nonorthogonal Filter Banks‟, IEEE Transactions on Image Processing, vol. 22, pp.1005-1017.

25. Eskicioglu, AM & Fisher, PS 1995, „Image Quality Measures and their Performance‟, IEEE Transactions on Communications, vol. 43, no. 12, pp. 2959-2965.

26. Flusser, J, Sroubek, F & Zitov B 2007, „Image Fusion: Principles, Methods, and Applications‟, Lecture notes, Tutorial EUSIPCO.

27. Fowler, J 2005, „The Redundant Discrete Wavelet Transform and Additive Noise‟, IEEE Signal Processing Letters, vol. 12, no. 9, pp. 629- 632.

28. Garg S, Ushah Kiran K, Mohan R & Tiwary U 2005, „Multilevel Medical Image Fusion using Segmented Image by Level Set Evolution with Region Competition‟, 27th Annual Conference IEEE Engineering in Medicine and Biology, vol. 7, pp. 7680-7683.

29. Gonzalez, RC & Woods, RE 2002, Digital Image Processing, 2nd Edition, Prentice Hall, New Delhi.

30. Guihong, Q, Dali, Z & Pingfan, Y 2001, „Medical Image Fusion by Wavelet Transform Modulus Maxima‟, Optics Express, vol. 9, pp.184-190.

31. Guo, Y & Huang, Y 2016, „A Medical Image Fusion Algorithm Based on Multi-channel PCNN in NSCT Domain‟, International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 9, no. 3, pp. 367-382.

32. Guruprasad, S, Kurian, MZ & Suma, HN 2015, „Fusion of CT and PET Medical Images Using Hybrid Algorithm DWT-DCT-PCA‟, 2ndInternational Conference on Information Science and Security (ICISS), pp.1-5

33. Himanshi, Bhateja, V, Krishn & Sahu, A 2016, „Medical Image fusion in Curvelet Domain Employing PCA and Maximum Selection Rule‟, 2nd International Conference on Computers and Communication Technologies, Advances in Intelligent Systems and Computing, vol. 379, Springer, New Delhi.

34. http://www.med.harvard.edu/aanlib/

35. https://en.wikipedia.org/wiki/Medical_imaging

36. http://sperling prostatecenter.com

37. https://www.snmmi.org

38. http://www. healthofchildren.com

39. http://www. mayoclinic.org

40. James, AP & Dasarathy, BV 2014, „Medical Image Fusion: A survey of state of the art‟, Information Fusion, vol. 19, pp. 4-19.

41. Jayaraman, S, Esakkirajan, S, Veerakumar, T 2009, Digital Image Processing, TMH, New Delhi.

42. Jianhui, S, Jing, G & Yanju, L 2015, „Fusion of Infrared and Visible Images Based on Pulse Coupled Neural Network and Nonsubsampled Contourlet Transform‟, The Open Cybernetics & Systemics Journal, vol. 9, pp. 17-22.

43. Kumar, M, Ramuhalli, P & Dass, S 2009, „A Total Variation Based

Algorithm for Pixel Level Image Fusion‟, IEEE Transactions on Image Processing, vol. 18, no. 9, pp. 2137-2143.

44. Li Xu, Roux, M, Mingyi, H & Schmitt, F 2008, „A New Method of Image Fusion Based on Redundant Wavelet Transform‟, 5th International conference on Visual Information Engineering, pp. 12-17.

45. Li, H, Manjunath, BS & Mitra, SK 1994, „Multi-Sensor Image Fusion using the Wavelet Transform‟, IEEE International Conference on Image Processing (ICIP), vol. 1, pp. 51-55.

46. Li, M, Cai, W & Tan, Z 2006, „A Region-Based Multi-Sensor Image Fusion Scheme using Pulse-Coupled Neural Network‟, Pattern Recognition Letters, vol. 27, pp. 1948-1956.

47. Li, M, Zhang, XY & Mao, J 2008, „Neighboring Region Variance Weighted Mean Image Fusion based on Wavelet Transform‟, Foreign Electronic Measurement Technology, vol. 27, no. 1, pp. 5- 6.

48. Li, S & Yang, B 2008, „Multifocus Image Fusion using Region Segmentation and Spatial Frequency‟, Image and Vision Computing, vol. 26, no. 7, pp. 971-979.

49. Li, S, Kwok, JT & Wang, Y 2001, „Combination of Images with Diverse Focuses Using Spatial Frequency‟, Information Fusion, vol. 2, pp. 169-176.

50. Li, W, Zhu, X & Wu, S 2006, „A Novel Approach to Fast Medical Image Fusion Based on Lifting Wavelet Transform‟, The Sixth World Congress on Intelligent Control and Automation (WCICA 2006), Dalian, vol.2, pp.9881-9884.

51. Li, ST, Kang, XD & Hu, JW 2013, „Image fusion with Guided Filtering‟, IEEE Transactions on Image Processing, vol. 22, no. 7, pp. 2864-2875.

52. Li, T & Wang, Y 2011, „Biological image fusion using a NSCT based variable-weight Method‟, Information Fusion, vol.12, no.2,pp.85–92.

53. Li, Y & Liu, G 2009, „Cooperative Fusion of Stationary Wavelet Transform and Non-subsampled Contourlet for Multifocus Images‟, Second International Symposium on Computational Intelligence and Design, vol. 1, pp. 314-317.

54. Licai, Y, Xin, L & Yucui, Y 2008, „Medical Image Fusion based on Wavelet Packet Transform and Self-Adaptive Operator‟, In Proceedings of International Conference on Bioinformatics and Biomedical Engineering, pp. 2647-2650.

55. Liu, GX & Yang, WH 2002, „A Wavelet-Decomposition-Based Image Fusion Scheme and its Performance Evaluation‟, Acta Automatica Sinica, vol. 28, no. 6, pp. 927-934.

56. Liu, H 2012, „Image Fusion Method based on Non-Subsampled Contourlet Transform‟, Journal of Software, vol. 7, no. 12, pp. 2816-2822.

57. Liu, SQ, Zhao, J, Geng, P, Xiuling , L & Yuchao, S 2014, „Medical Image Fusion based on Nonsubsampled Direction Complex Wavelet Transform‟, International Journal of Applied Mathematics and Machine Learning, vol. 1, no. 1, pp. 21-34.

58. Liu, Z, Yin, H Chai, Y & Yang, SX 2014, „A Novel Approach for Multimodal Medical Image Fusion‟, Expert Systems with Applications, vol. 14, no. 16, pp. 7425-7435.

59. Luna, A, Vilanova, JC, Hygino Da Cruz Jr., LC, Rossi, SE (Eds.) 2014, „Functional Imaging in Oncology: Biophysical Basis and Technical Applications‟, vol.1, Springer, Berlin.

60. Maes, F, Vandermeulen, D & Suetens, P 2003, „Medical Image Registration using Mutual Information", Proceedings of the IEEE, vol. 91, no. 10, pp. 1699-1721.

61. Mallat, SG 1989, „A theory of multiresolution signal decomposition: the wavelet representation", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 11, pp. 674-693.

62. Mazaheri, S, Sulaiman, PS, Wirza, R, Dimon, MZ, Khalid, F & Tayebi, RM 2015, „Hybrid Pixel-Based Method for Cardiac Ultrasound Fusion Based on Integration of PCA and DWT", Computational and Mathematical Methods in Medicine, vol. 2015, Article ID 486532, 16 pages.

63. Mitchell, HB 2010, Image Fusion: Theories, Techniques and Applications, Springer Science & Business Media.

64. Mitianoudis, N & Stathaki,T 2007, „Pixel-Based and Region-Based Image Fusion Schemes using ICA bases", Information Fusion**,** vol. 8, no. 2, pp. 131-142.

65. Moin, A, Bhateja, V & Srivastava, A 2016, „Weighted-PCA Based Multimodal Medical Image Fusion in Contourlet Domain", In: Satapathy, S, Bhatt, Y, Joshi, A, Mishra, D (eds), Proceedings of the International Congress on Information and Communication Technology, Advances in Intelligent Systems and Computing, vol. 439, Springer, Singapore, pp. 597-605.

66. Nain, N, Laxmi, V, Jain, AK & Agarwal, R 2006, „Morphological edge detection and corner detection algorithm using chain encoding", IPCV, vol. 6, pp. 520-525.

67. Nandeesh MD & Meenakshi, M 2015, „Image Fusion Algorithms for

Medical Images-A Comparison‟, Bonfring International Journal of Advances in Image Processing, vol. 5, no. 3, pp. 23-26.

68. [Online]. Available: http://www.metapix.de/fusetool.zip

69. Pajares, G & Cruz, JMDL 2004, „A Wavelet-Based Image Fusion Tutorial‟, Pattern Recognition, vol. 37, pp. 1855-1872.

70. Parmar, K & Kher, R 2012, „A Comparative Analysis of Multimodality Medical Image Fusion Methods‟, Sixth Asia International Conference on Modeling and Simulation, pp. 93-97.

71. Petrovic, VS & Xydeas, CS 2004, „Gradient-based Multiresolution Image Fusion‟, IEEE Transactions on Image Processing, vol. 13, no. 2, pp. 228- 237.

72. Piella, G 2003, „A General Framework for Multiresolution Image Fusion: From Pixels to Regions‟, Information Fusion, vol. 4, no. 4, pp. 259-280.

73. Pradhan, PS, King, RL, Younan, NH & Holcomb, DW 2006, „Estimation of the Number of Decomposition Levels for a Wavelet- based Multiresolution Multisensor Image Fusion‟, IEEE Transactions on Geoscience and Remote Sensing, vol. 44, no. 12, pp. 3674-3686.

74. Pradhan, R, Pradhan, P, Bhattacharjee, R & Singh, D 2014, „Edge Detection using Morphological Operator: A New Approach‟, International Journal of Advanced Research in Computer Science and Software Engineering, vol. 4, no. 2, pp. 84-88.

75. Pu, T & Ni, G 2000, „Contrast-Based Image Fusion using the Discrete Wavelet Transform‟, Optical Engineering, vol. 39, no. 8, pp. 2075- 2082.

76. Qu, XB, Yan, JW, Xiao, HZ & Zhu, ZQ 2008, „Image Fusion Algorithm Based on Spatial Frequency-Motivated Pulse Coupled Neural Networks in Nonsubsampled Contourlet Transform Domain‟, Acta Automatica Sinica, vol. 34, pp. 1508-1514.

77. Rana, A & Arora, S 2013, „Comparative Analysis of Medical Image Fusion‟, International Journal of Computer Applications, vol. 73, no. 9,pp.10-13.

78. Redondo, R, Sroubek, F, Fischer, S & Cristóbal, G 2008 „Multifocus Image Fusion using the log-Gabor transform and a Multisize Windows Technique‟, Information Fusion, vol. 10, no. 2, pp. 163-171.

79. Shen, R, Cheng, I & Basu, A 2012, „Cross-Scale Coefficient Selection for Volumetric Medical Image Fusion‟, IEEE Transactions on Biomedical Engineering ,vol.60, issue.4, pp.1069 -1079.

80. Shi, WZ, Zhu. CQ, Tian, Y & Nichol, J 2005, „Wavelet-based image fusion and quality assessment‟, International Journal of Applied Earth Observation and Geoinformation, vol. 6, no. 3-4, pp. 241-251.

81. Singh, R & Khare, A 2014, „Redundant discrete wavelet transform based medical image fusion‟, in proc. of International Symposium on Signal Processing and Intelligent Recognition Systems (SIRS-2014), in Advances in Intelligent Systems and Computing, Trivandrum, India , vol. 264, pp. 505-515.

82. Singh, S, Gupta, D, Anand, RS & Kumar, V 2015, „Nonsubsampled Shearlet based CT and MR Medical Image Fusion using Biologically Inspired Spiking Neural Network‟, Biomedical Signal Processing and Control, vol. 18, pp. 91-m,101.

83. Singh, R, Vatsa, M & Noore, A 2009, „Multimodal Medical Image Fusion using Redundant Discrete Wavelet Transform", Seventh International Conference on Advances in Pattern Recognition, pp. 232-235.

84. Soma Sekhar, A & Giri Prasad, MN 2011, „A Novel Approach of Image Fusion on MR and CT Images using Wavelet Transforms", 3rd International Conference on Electronics Computer Technology, vol. 4, pp. 172 - 176.

85. Sravya, K, Govardhan, P & Naresh Goud, M 2014, „Image Fusion on Multifocused Images using NSCT", International Journal of Computer Science and Information Technologies, vol. 5, no. 4, pp. 5393-5396.

86. Srinivasa Rao, D, Seetha, M & Krishna Prasad, MHM 2012, „Comparison of Fuzzy and Neuro Fuzzy Image Fusion Techniques and Its Applications", International Journal of Computer Applications, vol. 43, no. 20, pp. 31-37.

87. Tank, VP, Shah, DD, Vyas, TV, Chotaliya,SB & Manavadaria, MS 2013, „Image Fusion Based on Wavelet and Curvelet Transform", IOSR Journal of VLSI and Signal Processing (IOSR-JVSP), vol.1, issue. 5, pp.32-36.

88. Toet, A 1989, „A Morphological Pyramidal Image Decomposition", Pattern Recognition Letters, vol. 9, no. 4, pp. 255-261.

89. Toet, A, Van Ruvan, LJ & Valeton, JM 1989, „Merging thermal and visual images by a contrast pyramid", Optical Engineering, vol.28, no.7, pp.789-792.

90. Mantale, UB & Gaikwad, VB 2013, „Image Fusion of Brain Images using Redundant Discrete Wavelet Transform", International Journal of Computer Applications , vol.74, no.4, pp.7-11.

91. Wan-Qiang, Y & Chun-Sheng, Z 2008, „Multi-Spectral Image Fusion Method based on Wavelet Transformation", The International archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVII, no. Part B7, pp. 1261-1266.

92. Wang, A, Qi, C, Dong, L, Meng, S & Li, D 2013, „Multimodal Medical Image Fusion in Nonsubsampled Contourlet Transform Domain", IEEE International Conference on Measurement, Information and Control, vol. 1, pp. 169-172.

93. Wang, A, Sun, H & Guan, Y 2006, „The Application of Wavelet Transform to Multi-modality Medical Image Fusion", Proceedings of the IEEE International Conference on Networking, Sensing and Control, pp. 270-274.

94. Wang, L, Li, B & Tian, L 2014, „EGGDD: An explicit dependency model for multi-modal medical image fusion in shift-invariant shearlet transform domain", Information Fusion, vol. 19, pp.29-37.

95. Wang, N, Ma, Y, Zhan, K & Yuan, M 2013, „Multimodal Medical Image Fusion Framework based on Simplified PCNN in Nonsubsampled Contourlet Transform Domain", Journal of Multimedia, vol. 8, no. 3, pp. 270-276.

96. Xydeas, CS & Petrovi, V 2000, „Objective Image Fusion Performance Measure", Electronics Letters, vol. 36, no. 4, pp. 308-309.

97. Yang, J, Ma, Y, Yao, W, & Lu, WT 2008, „A Spatial Domain and Frequency Domain Integrated Approach to Fusion Multifocus Images", The International Archives of the Photogrammetry, Remote Sensing and Spatil Information Sciences, vol. XXXVII, no. B7, pp. 1147-1150.

98. Yang, Y, Tong, S, Huang, S & Lin, P 2014, „Log-Gabor Energy Based Multimodal Medical Image Fusion in NSCT Domain", Computational and Mathematical Methods in Medicine , vol. 2014, Article ID 835481, 12 pages.

99. Yang, Y, Huang, S, Gao, J, & Qian, Z 2014, „Multi-focus Image Fusion using an Effective Discrete Wavelet Transform based Algorithm", Measurement Science Review, vol. 14, no. 2, pp. 102-108.

100. Yang, Y, Park, DS, Huang, S & Rao, N 2010, „Medical Image Fusion via an Effective Wavelet-Based Approach", EURASIP Journal on Advances in Signal Processing, Article ID 579341, pp.1-13(13 pages).

101. Yang, Y, Park, DS, Huang, S, Fang, Z & Wang, Z 2009, „Wavelet based Approach for Fusing Computed Tomography and Magnetic Resonance Images", Control and Decision Conference (CCDC "09), Chinese, pp. 5770-5774.

102. Yazdi M & Ghasrodashti, EK 2012, „Image Fusion based on Non-Subsampled Contourlet Transform and Phase Congruency", IEEE 19th International Conference on Systems, Signals and Image Processing, pp.616-620, pp. 11-13.

103. Yu L, Zu D, Wang W & Bao S 2001, „Multi-modality medical image fusion based on wavelet analysis and quality evaluation", Journal of Systems Engineering and Electronics,vol.12, no.1, pp.42-48.

104. Zanxia, Q, Jiaxiong, P & Hongqun, W 2003, „Remote Sensing Image

105. Fusion Based on Small Wavelet Transform's Local Variance‟, Journal of Huazhong University of Science and Technology: Natural Science, vol. 6, pp. 89 - 91.

106. Zaveri, T & Zaveri, M 2011, „A Novel Region Based Multimodality Image Fusion Method‟, Journal of Pattern Recognition Research, vol. 6, no 2, pp.140-153.

107. Zheng, Y, Essock, EA, Hansen, BC & Haun, AM 2007, „A New Metric Based on Spatial Frequency and Its Application to DWT Based Fusion Algorithm‟, Information Fusion, vol. 8, pp. 177-192.

108. Zhang, Z & Blum, RS 1999, „A Categorization of Multiscale-Decomposition-Based Image Fusion Schemes with a performance study for a Digital Camera Application‟, Proceedings of the IEEE, vol. 87, no. 8, pp. 1315-1326.

APPENDIX:

Matlab code:

```
clc;

 clear all;

 close all;

%% Inputs

% fp=uigetfile('*.bmp'); fp=uigetfile('.jpg;.bmp'); I=imread(fp);

%I=rgb2gray(I);

% I=imresize(I,[256 256]); if size(I,3)>1

I = rgb2gray(I);

end figure; imshow(I);

title('Image1');

% fp=uigetfile('*.bmp'); fp=uigetfile('.jpg;.bmp'); J=imread(fp);

%J=rgb2gray(J);

% J=imresize(J,[256 256]); if size(J,3)>1

J = rgb2gray(J);

end figure; imshow(J);

title('Image2');

%%

%  Parameteters:

nlevels = 0; %[0, 1, 3] ;
```

```
% Decomposition level pfilter = 'maxflat' ;     % Pyramidal filter

dfilter = 'dmaxflat7' ; % Directional filter dmaxflat7

% build mex

% build lib

yj = nsctdec( double(J), nlevels, dfilter, pfilter ); yi = nsctdec( double(I), nlevels, dfilter, pfilter );

% [A1,H1,V1,D1] = dwt2(yi{1,1},'sym4','mode','per');

% [A2,H2,V2,D2] = dwt2(yj{1,1},'sym4','mode','per'); [A1,H1,V1,D1] = dwt2(yi{1,1},'sym4');

[A2,H2,V2,D2] = dwt2(yj{1,1},'sym4');

% [A1,H1,V1,D1] = dwt2(yi{1,1});

% [A2,H2,V2,D2] = dwt2(yj{1,1}); A=A1+A2;

[s1, s2]=size(A1);

for i=1:s1 for j=1:s2

if(H1(i,j)>=H2(i,j))

H(i,j)=H1(i,j);

else

H(i,j)=H2(i,j);

end end

end

for i=1:s1
```

```
for j=1:s2 if(V1(i,j)>=V2(i,j))

V(i,j)=V1(i,j);

else

V(i,j)=V2(i,j);

end end

end

for i=1:s1 for j=1:s2

if(D1(i,j)>=D2(i,j))

D(i,j)=D1(i,j);

else

D(i,j)=D2(i,j);

end end

end

y{1,1} = idwt2(A,H,V,D,'sym4');

y{1,2}=yj{1,2}+yi{1,2};

% x = nsctrec(y, [dfilter, pfilter] );

% x = nsctrec(y, 'maxflat7', 'dmaxflat7');

% x = nsctrec(y, maxflat7, dmaxflat7);

Final = nsctrec(y);

Final=mat2gray(Final); figure;

imshow(Final); title('Fused Image');
```

```
%% Performance measuring ent=entropy(Final); fprintf('ENTROPY=%f',ent);

% I=double(rgb2gray(I)); I=double((I));

% Final=rgb2gray(Final);
% Final=uint8(Final); psnr1=psnr(I, Final); fprintf('\nPSNR1=%f',psnr1);

% J=double(rgb2gray(J)); J=double((J));

psnr2=psnr(Final, J); fprintf('\nPSNR2=%f',psnr2);

Finalg=double(Final); SDE=std(Finalg); SDE=mean(SDE);

fprintf('\nStandard Devation=%f',SDE);
```

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