Spatial Frequency Discrete Wavelet Transform Based Image Fusion Technique for CT and MRI Images

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Abstract— **Medical imaging plays a significant part in many applications of medical diagnosis and therapy in today's technologically advanced era. For effective medical diagnosis, more accurate images with much more details and information are required. There are numerous medical modalities available nowadays that provide valuable information about various diseases. Computed Tomography (CT) images, for illustration, provide more information on dense tissues such as bones, whereas Magnetic Resonance (MR) images provide more information on soft tissues. However, for disease diagnosis, a single modality cannot deliver high spatial resolution and visualisation of medical images. Medical image fusion, which use image processing techniques to merge multi-modal images, could be a useful tool in this area. The suggested Spatial Frequency DWT-DCT (SFDWT-DCT – Spatial Frequency Discrete Wavelet Transform with Discrete Cosine Transform) technique is used to develop a multiresolution image fusion method. The low resolution MRI image is resampled to the high resolution CT image in the SF-DWT-DCT technique, and fusion is performed by injecting the spectral and spatial information present in CT and MRI images onto each other utilising their corresponding DWT-DCT coefficients by analysing the spatial frequency (SF). The source images are derived from MR and CT imaging modalities. The experimental results show that the suggested method outperforms other methods on subjective and objective measures such as Entropy (EN), Mutual Information (MI), and Structural Similarity Index Measure (SSIM), among others.**

Index Terms— CT & MRI Image Fusion, SFDWT, ASD, PSNR, SSIM, Spatial frequency etc

I. Introduction

Medical imaging has been the most critical and vital part of modern health care practices. Now a day, medical image processing plays a significant role in the patient management system starting from diagnosis to post-treatment analysis. The diagnosis of the disease involves non-invasive acquisition of information about the human body organs through imaging. There are many modalities available for capturing the data from affected part of the body. These are based on the physics used in the acquisition process. The source of imaging is x-rays (radio graph, computed tomography (CT)), ultrasound (ultrasound guided imaging (USG)), magnetism (magnetic resonance imaging (MRI), functional magnetic resonance imaging (fMRI)), light (optical coherence tomography (OCT)), gamma rays for radioactive isotopes (positron emission tomography (PET) and single-photon emission computed tomography (SPECT)) etc. [1, 2]. Every modality provides different representation of the abnormalities depending on its acquisition technique as shown in Figure 1. Computed tomography (CT) provides the information related to calcifications, bone structures, tumour outline prominently. Magnetic resonance imaging (MRI) is the best modality for soft tissue anatomy. It displays the lesions distinctly. It helps in diagnosis of diseases related to soft tissues, extent of lesions, etc. PET and SPECT images give abnormal metabolism at cancer infected tissues. However, CT has poor contrast for soft tissues and MRI cannot detect calcifications. PET and SPECT have very poor spatial and structural discrimination. Thus, every modality may not exhibit all the necessary information related to a particular disease. Therefore, physicians always recommend subjects to undergo various modalities imaging before making the final diagnosis.

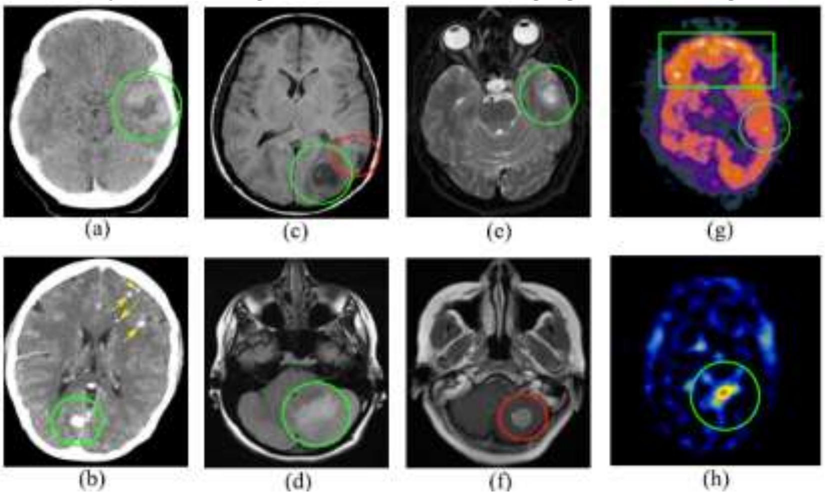


Figure 1: Medical image modalities and their ability to represent abnormalities in brain

The development of multimodality imaging sensors for capturing information has influenced to explore the possibility of data reduction and having better visual representation. Image fusion [3, 4] is one way to achieve this. The objective of image fusion [5, 6] is to merge complementary information from multiple registered source images into single composite image for better perceptual and visual representation. More precisely, image fusion can be defined as a process of visualization of a multi-valued image with a single-valued image [7]. Fusion of multimodal, multifocus, multitemporal images is highly required since one kind of imaging sensor is not able to provide all information from source images. For example, visible and thermal imaging sensors, having different and complementary information are successfully used for fusion to elicit all the pertinent information.

Multimodality image fusion has been proved advantageous as it provides more accurate and non-redundant information in less time with reduced cost and storage. Therefore, the concept of image fusion has been explored in a variety of potential applications such as concealed weapon detection [8], remote sensing [9], military surveillance [10], image retrieval, object tracking , object recognition, information security and biometrics.

Fusion two or more images of the same scene and modality, each of them blurred and noisy, may lead to a deblurred and denoised image. Multichannel deconvolution is a typical representative of this category. This approach can be extended to superresolution fusion, where input blurred images of low spatial resolution are fused to provide us a high-resolution image.

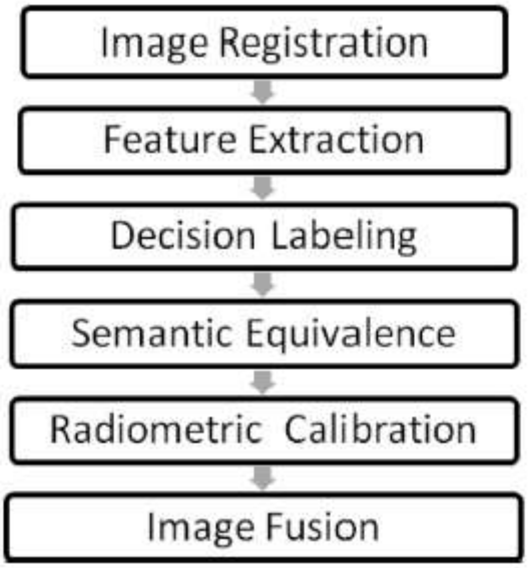


Figure 2: Main steps of image fusion

In each category, the fusion consists of two basic stages: image registration, which brings the input images to spatial alignment, and combining the image functions (intensities, colors, etc) in the area of frame overlap. Image registration works usually in four steps,

- **Feature detection**
- **Feature matching**
- **Transform model estimation**
- **Image resampling and transformation**

Medical image processing [12] is a rapidly growing area of research for the last three decades. X-ray, ultrasound, MRI (magnetic resonance imaging) and CT (computed tomography) are a few examples of medical imaging sensors which are used for extracting clinical information. These sensors provide complementary information about patient's pathology, anatomy, and physiology. For example, X-ray is widely used in detecting fractures and abnormalities in bone position, CT is used in tumor and anatomical detection and MRI is used to obtain information about tissues. Similarly, other medical imaging techniques like fMRI (functional magnetic resonance imaging), PET (positron emission tomography), SPECT (single positron emission computed tomography) provide functional and metabolic information [13]. Further, T1-MRI image provides details about anatomical structure of tissues whereas T2-MRI image gives information about normal and abnormal tissues.

BRAIN IMAGING MODALITY

Modern imaging methods provide the opportunity for non-invasive in vivo study of human organs and can provide measurements of local neuronal activity of the living human brain. These imaging modalities can be divided into two global categories namely functional imaging and structural imaging.

Functional modalities include SPECT and Positron Emission Tomography (PET) (known as nuclear medicine imaging modalities), and Functional Magnetic Resonance Imaging (fMRI). Electro encephalaography (EEG), Magneto encephalography (MEG) and Electrical Impedance Tomography (EIT) can also be named as a functional imaging technique.

Structural imaging represents a range of measurement techniques which can display anatomical information. These modalities include X-ray, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) [14].

Magnetic Resonance Imaging (MRI): Magnetic Resonance Imaging (MRI) is a method used for looking inside the body without using surgery or X-rays. MRI has become firmly established as the premier diagnostic modality for the head as stated by Val. It uses magnetism and radiowaves to produce clear pictures of the human anatomy.

MRI is a powerful visualization technique that allows images of internal anatomy to be acquired in a safe and non-invasive way. It is based on the principles of Nuclear Magnetic Resonance (NMR). The ability of MRI to record signals that can distinguish between different soft tissues such as GM and WM. This is being used in evaluating brain tumors as stated by Brown & Semoka [15].

MR based imaging techniques are used to characterize brain tumors according to their anatomy and physiology, particularly clinicians are interested in determining the tumor location, extent, amount of necrosis, vascular supply and associated edema.

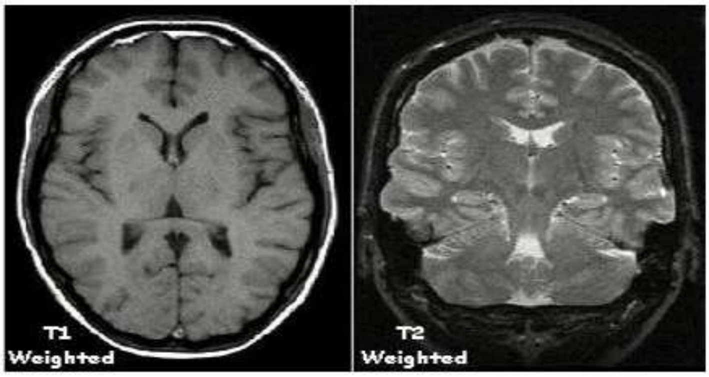


Figure 3: MRI of brain

Functional Magnetic Resonance Imaging (fMRI): Functional magnetic resonance imaging (fMRI) is a rapidly growing field which uses MRI equipment for visualizing human parts in three dimensional and multi dimensional space. Challenging fields like, identifying changes in complex brain structure and morphological variations in surface of the brain, analyzing similar features among group of subjects brain and its interlinks with specific diseases, identifying motor and sensory response of the brain with respect to the behavior/external stimuli can be effectively handled with the help of fMRI. Most of the methods are based on Blood Oxygen Level Dependent (BOLD) contrast which uses magnetic susceptibility of Hemoglobin (Hb). Even a small difference in magnetic susceptibility results significant difference in susceptibility-weighted MR image intensity of brain [16].

Computed Tomography (CT): Computed Tomography (CT), originally known as Computed Axial Tomography (CAT) and body section roentgenographys, is a medical method employing tomography where digital geometry processing is used to generate a three dimensional image of the internals of an object from a large series of two dimensional image taken around a single axis of rotation. CT produces a series of axial images which can be manipulated, through a process known as windowing, in order to recreate the image in a different plane. The CT scan brain image is shown in figure 4.

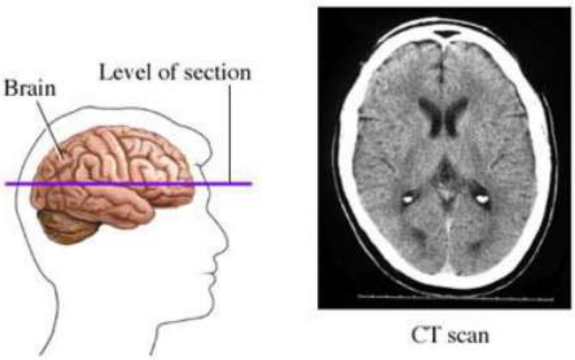


Figure 4: CT scan of brain

Diagnosis of cerebrovascular accidents and intracranial hemorrhage is the most frequent reason for a head CT or CT brain. Scanning is done with or without intravenous contrast agents. CT generally does not exclude infract in the acute stage of a stroke, but is useful to exclude a bleed. For detection of tumors, CT scanning with intravenous contrast is occasionally used but is less sensitive than MRI.

Application Areas of Image Fusion

IF has been widely used in many different applications such as,

- Remote Sensing Applications
- Medical Domain Applications
- Surveillance Domain Applications
- Photography Domain Applications
- Recognition Application
- Detection and Tracking Application

II. Literature Review

The medical image fusion process has been evolved faster over last two decades. Although it had been a centre of attraction, its efficient use in clinical applications is awaited. The reasons behind the progress of this technology so far are its applicability in clinical use, feasibility in developing algorithms, and unavailability of hybrid acquisition machines.

The process has been popular for diagnosis, prognosis, treatment, and analysis. The fusion process utilizes variety of image data sets and information representations. The methods are typically based on the process of combining complementary and relevant information from two or more image data sets into visually better image as compared with source modalities. The large number of techniques, algorithms, methodologies, and processes has been developed all over the world. This chapter deals with the development of fusion algorithms especially medical image fusion era in the view of feature extraction which is related to the proposed work in this paper.

CT and MRI fusion using morphological operators has mixed success rate [17]. However, morphological implementations provide simple design and real time fusion advantage provided the source images are coregistered. The success of such fusion is depend on selection of structuring element and its size and spatial resolution of source images. Wavelet domain fusion schemes are robust as they represent coarser and fine details separately with sparse representation for point singularities. Variety of fusion schemes using wavelet are presented in literature. The attractive applications of fusion in clinical practice are brain tumor segmentation, cancer diagnosis, radiotherapy treatment planning. Wavelet features extraction combined with classifiers like neural networks improve the robustness of fusion process. It helps in reduction in fusion time and feature vector length. Few examples are wavelet with entropy, with shift invariant morphological fusion, with independent component analysis (ICA), with contourlet transform based on PCA [18], etc.

Yang et al. implemented the pixel level decomposition on weighted average fusion rule in wavelet domain [19]. PCA based fusion in wavelet domain and in Ridgelet Domain has been also explored. Multiresoltuion techniques (pyramid and wavelet transforms) have been widely used and preferred for image fusion. Pyramid transforms such as Laplacian pyramid, ratio of low pass pyramid, and contrast pyramid have been commonly used for image fusion in initial phase of research work. The pyramid transforms has blocking artefacts in fused images due to which wavelet transform based multiresolution analysis approach is prefered by researcher for fusion recently. The most common and easy fusion process is in discrete wavelet transform (DWT) domain. Many the other wavelet transforms popularly used for medical image fusion such as lifting wavelet transform (LWT), undecimated wavelet transform (UDWT), curvelet transform (CVT), contourlet transform and nonsubsampled contourlet transform (NSCT). Some of these fusion techniques are found [20]. These simple wavelet transforms as well as advanced wavelet transforms su_er due to shift variance, limited directional selectivity, and no phase information. Singh et al. used dual tree complex wavelet transform (DTCWT) and Daubechies complex wavelet transform (DCxWT) for image fusion with notable fusion performance [21]. Discrete Wavelet packet transform based fusion is also attempted. A image fusion scheme using lifting wavelet transform along with new fusion rules has been presented. Low frequency coefficients are selected based on regional character and high frequency coefficients are used based on directional characteristics and quad tree structure of wavelet.

Physicians are using a fusion of PET and CT images for better visualization of the infected tissue activities. The algorithms used were weighted wavelet coefficients and multiwavelet transform for PET-CT fusion. The use of hardware based and software based MMIF on PET and CT images in radiation therapy like image guided radiation therapy (IGRT), were discussed. PET-MRI fusion is also used for analysis of the effectiveness of 18F-FDG in nuclear medicine treatment protocols. The shift-invariant shearlet transform and Hidden Markov Model is efficiently used for MRI-PET and MRI-SPECT fusion [22]. Fuzzy based fusion and wavelet based fusion of local features from PET and MRI are presented.

Hao Chen et al. have developed a fusion algorithm using wavelet packets transform for visual and infrared (IR) spectrum satellite images [23]. Integer wavelet transform is used to get features from anatomical and functional images and combined these images using neuro-fuzzy approach is presented. Ripplet transform based MMIF technique is developed by Das et al. [23]. Ali et al. used curvelet transform for fusion of CT and MRI images. The nonsubsampled contourlet transform (NSCT) is also offer promising results for the medical image fusion. It is proved to be much effective when fused with the help of neuro-fuzzy approach.

Neural network based fusion rules are used to improve the fusion result [24]. The neural network based fusion is also combined with other techniques to increase the selection of features and decision making ability of algorithm. Few such examples of fusion are neural network with fuzzy logic, wavelet features trained with neural network to enhance quality of an image, neural network combined with support vector machines, (SVM) and Gaussian mixture model, (GMM). Discrete wavelet transform is used for feature extraction and the fusion results are optimized using genetic algorithm. Multimodality image fusion using mutual information and genetic algorithm also provide good fusion performance. The fusion of infrared (IR) and visible images using DTCWT based feature extraction and fuzzy logic based fusion rules is achieved effectively.

- **Multisensor Image Fusion and Enhancement in Spectral Total Variation Domain (Wenda Zhao 2017)**

Most existing image fusion methods assume that at least one input image contains high-quality information at any place of an observed scene. Thus, these fusion methods will fail if every input image is degraded. To address this issue, this study proposes a novel fusion framework that integrates image fusion based on spectral total variation (TV) method and image enhancement. For spatially varying multiscale decompositions generated by the spectral TV framework, this study verifies that the decomposition components can be modeled efficiently by the tailed Rayleigh distribution (TRD) rather than the commonly used Gaussian distribution. Consequently, salience and match measures based on TRD are proposed to fuse each sub band decomposition. The spatial intensity information is also adopted to fuse the remainder of the image decomposition components. A subband adaptive gain function family based on TV spectrum and space variation is constructed for fused multiscale decompositions to enhance fused image simultaneously. Finally, numerous experiments with various multisensor image pairs are conducted to evaluate the proposed method. Experimental results show that even if the input images are degraded, the fused image obtained by the proposed method achieves significant improvement in terms of edge details and contrast while extracting the main features of the input images, thereby achieving better performance compared with the state-of-the-art methods [103].

- **A total variation spectral framework for scale and texture analysis (G. Gilboa, 2014)**

A spectral TV method was successfully applied to image decomposition, in which a notion of generalized nonlinear eigenfunctions was presented to define forward and inverse TV transforms. On the basis of this method, an effective texture decomposition method was achieved. Motivated by these works, the current study adopts the spectral TV framework to conduct image fusion and enhancement [25].

- **Spectral Total-Variation Local Scale Signatures for Image Manipulation and Fusion (Ester Hait 2018)**

He propose a unified framework for isolating, comparing and differentiating objects within an image. We rely on the recently proposed total-variation transform, yielding a continuous, multi-scale, fully edge-preserving, local descriptor, referred to as spectral total-variation local scale signatures. We show and analyze several useful merits of this framework. Signatures are sensitive to size, local contrast and composition of structures; are invariant to translation, rotation, flip and linear illumination changes; and texture signatures are robust to the underlying structures. We prove exact conditions in the 1D case. We propose several applications for this framework: saliency map extraction for fusion of thermal and optical images or for medical imaging, clustering of vein-like features and size-based image manipulation [26].

- **Fusion of Multispectral and Panchromatic Images Based on Morphological Operators (Rocco Restaino 2016)**

Nonlinear decomposition schemes constitute an alternative to classical approaches for facing the problem of data fusion. In this paper, we discuss the application of this methodology to a popular remote sensing application called pansharpening, which consists in the fusion of a low resolution multispectral image and a high-resolution panchromatic image. We design a complete pansharpening scheme based on the use of morphological half gradient operators and demonstrate the suitability of this algorithm through the comparison with the state-of-the-art approaches. Four data sets acquired by the Pleiades, Worldview-2, Ikonos, and Geoeye-1 satellites are employed for the performance assessment, testifying the effectiveness of the proposed approach in producing top-class images with a setting independent of the specific sensor [27].

- **Image fusion with guided filtering (S. Li, X. Kang 2013)**

A fast and effective image fusion method is proposed 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 is proposed to make full use of spatial consistency for fusion of the base and detail layers. Experimental results demonstrate that the proposed method can obtain state-of-the-art performance for fusion of multispectral, multifocus, multimodal, and multiexposure images.

III. Adaptive Structure Decomposition (ASD)

There are three key steps in this method (as in figure 5). First, based on the different scales of issues, we self-adaptively decompose source images into corresponding sub-bands with STV technique. In this way, we get the sub-bands with strong interpretability so that we can design an effective fusion method. Second, based on the interpretability of sub-bands, for the small scale and middle scale of issues, we extract the edge information from the sub-bands and design the weight of fusion by the local edge energy. And for the large scale of issues, we design the weight of fusion by the local intensity energy. Third, we reconstruct the fused image. Detailed instruction is presented below.

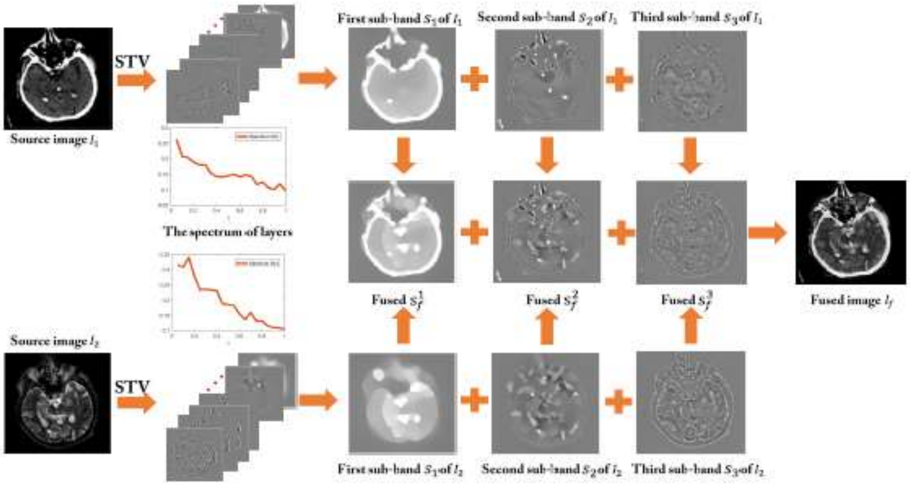


Figure 5: Schematic diagram of ASD based image fusion method

ADAPTIVE DECOMPOSITION METHOD

The computed tomography (CT) has an excellent performance on detecting dense structure such as bones and implants and magnetic resonance (MR) provides high-resolution information for soft issues. To enhance the interpretability of sub-bands and therefore design an effective fusion strategy, we decompose the source images according to the different scales of issues. The maxima values of TV spectrum often stand for the main scale feature components (as in figure 6). Therefore, on the basis of maxima values, we manage to design a adaptive decomposition to ensure every sub-band contains one of the two maximum values, which enhance the interpretability of the sub-bands[26].

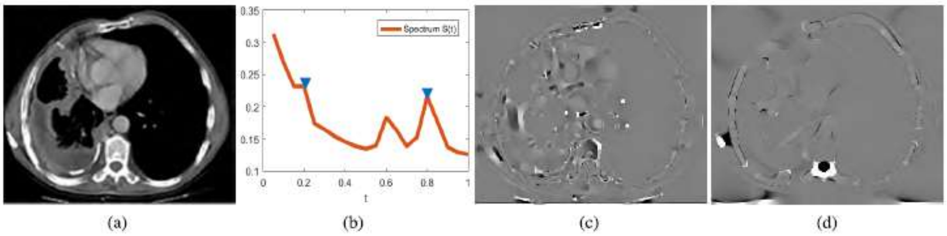


Figure 6: The spectrum of main feature layers and sub-bands divided

FUSION STRATEGY

The first sub-band (sub-band with large scale of issues) contains the intensity information of issues, so we fuse first subbands of two source images with local intensity energy (LIE). We take *pi* as the local energy of pixel *xi*:

$$p_i = \frac{1}{K}\sum_{i=1}^{K} G_{n*n}(x_i), \qquad (1)$$

where *Gn*n*(*) means Gaussian filtering with a window of *n *n*. And the weight of pixel *xi* of image *I*1 is

$$w_i^1 = \frac{p_i^1}{p_i^1 + p_i^2}. \qquad (2)$$

Therefore, the *i*-th pixel of the fusion result for the first subband *s*1 is

$$x_i^f = w_i^1 \times x_i^1 + w_i^2 \times x_i^2. \qquad (3)$$

RECONSTRUCTING FUSED IMAGE

Finally, we reconstruct the fused image with

$$I_f = s_f^1 + s_f^2 + s_f^3 \quad (4)$$

Where *sif* means the *i*-th sub-band of fusion result and *If* stands for the fused image.

IV. Performance Evaluation Metrics

A number of performance evaluation metrics have been anticipated to evaluate the performances of diverse IF techniques. They can be categorized as subjective and objective assessment measures. Subjective assessment measures play important role in IF as it evaluates the fused image quality based on human visual perception [27].

MSE (Mean Squared Error) and Peak signal to noise ratio (PSNR)

The term peak signal-to-noise ratio (PSNR) is an expressed as the ratio of maximum possible value of a signal and the power of distorting noise that affects the quality of its representation. The dimensions of the two images must be the same. Mathematical representation of the PSNR is as follows:

$$PSNR = 20log_2\left(\frac{MAX_f}{\sqrt{MSE}}\right) \quad (5)$$

Where the MSE (Mean Squared Error) is:

$$MSE = \frac{1}{mn}\sum_0^{m-1}\sum_0^{n-1}|f(i,j) - g(i,j)|^2 \quad (6)$$

Where, f is the matrix data of the original image, g is the matrix data of processed image, m and n represents the numbers of rows and the columns of pixels of the images and i and j represents the index of row and the column respectively. MAX_f is the maximum signal in image f.

Structural similarity index metric (SSIM)

SSIM computes the similarity between one or more images. It is designed by modeling any contrast distortion and radiometric. It is a combination of the luminance image distortion and the combination of contrast distortion, loss correlation and structure distortion between source images and the final image. This metric is defined as follow:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (7)$$

where the μx average of x, μy the average of y, σ_x^2 the variance of x, σ_y^2 the variance of y, σ_{xy} the covariance of x and y, $c1$ and $c2$ two variable to stabilize the division with the weak denominator.

Mutual Information (MI)

Mutual Information provides the Information quantity detail of source images, which are merged in the resultant image. The highest Mutual Information represents the effectiveness of the image fusion technique. This is defined as follows,

$$MI_{AF} = \sum_{a,f} P_{A,F}(a,f) log \left[\frac{P_{AF}(a,f)}{P_A(a)P_F(f)} \right] \quad (8)$$

Where $PA(a)$ and $PF(f)$ denote the marginal histogram of input image A and the fused image is F. PA, $F(a, f)$ indicate joint histogram of input image A and fused image is F. if mutual Information value is high it means fusion performance is good.

Entropy (EN)

It is used to evaluate the Information content of an image and it produce sensitive noise in the image. Image with large Information content has low cross entropy. This metric is defined as follow:

$$EN = -\sum_{l=0}^{L-1} p_l log_2 p_l \quad (9)$$

Where, L is denotes the total number of gray levels and pl denotes the normalized histogram of the corresponding gray level in the image fusion. If the EN value is higher it means it contains more Information and better performance in the image fusion.

V. Proposed Algorithm

In Image processing, fusion of MRI image and CT image is an important technique. This thesis incorporates a multiresolution image fusion algorithm based on the proposed Spatial Frequency DWT-DCT (SFDWT-DCT – Spatial Frequency Discrete Wavelet Transform with Discrete Cosine Transform) technique. In SF-DWT-DCT technique, the low resolution CT image is resampled to the high resolution MRI image and fusion is done by injecting the spectral and spatial information's present in CT and MRI images onto each other using their corresponding DWT-DCT coefficients by evaluating the spatial frequency (SF – Spatial Frequency).

Spatial Frequency DWT-DCT (SF-DWT-DCT) image fusion technique

Spatial frequency (SF) is a measure of the amount of frequency content which is present in the image. In other words, it shows the clarity or sharpness of the image. Moreover, urban and covers, which includes buildings, transportation, parks, stadiums etc. can be considered as high frequency content. Hence in such application preserving high frequency content is also important in addition to improving the spectral quality [28]. As explained earlier, SF is a parameter which is directly related to the high frequency content of the image. Thus SF can be used in the fusion of urban areas in remote sensing applications. The effect of SFDWT will be more predominant in images with large high frequency contents.

The technique proposed make use of DWT-DCT to extract the spatial information contained in CT image and MRI image and then it is combined using the new fusion rule which is based on spatial frequency to get the high-resolution images. In standard wavelet-based image fusion techniques, after finding the wavelet coefficients associated with the MRI image and CT image, the detail coefficients of CT image and approximation coefficient of MRI image are combined to obtain the fused image. It can be seen that, in most of the image fusion technique, the high frequency component of MRI image is replaced with that of the high frequency component of CT image and thus the details coefficients of MRI image are often discarded. There may be some useful information. present in the detail coefficients of MRI image which can be made use of. This is the motivation behind the proposed SFDWT image fusion technique.

Algorithm of SFDWT Image Fusion Technique,

(1) MRI image is resampled so that its spatial resolution is equal to that of the CT image in order to get a perfectly superimposable image.

(2) Apply DWT to MRI image and calculate the approximation and detail coefficients.

(3) Similarly apply DWT to CT image and decompose it into their respective approximation and detail coefficients.

(4) Approximation coefficient of CT image is replaced with that of MRI image.

(5) Each pair of the detail coefficients obtained in step (2) & (3) are fused by using the proposed fusion rule based on spatial frequency given in steps (6)–(10).

(6) CT Detail Coefficients (P_{DC}) is histogram matched with the intensity component of the MRI Detail Coefficients (M_{DC}).

(7) Spatial Frequency of both, histogram matched CT Detail Coefficients (F_{SPC}) and the intensity value of MRI Detail coefficients (F_{SMC}) are calculated using Eqs. (1)–(3).

(8) The Normalized spatial frequencies of the Intensity value of MS Detail Coefficients.

(9) The Normalized spatial frequencies of histogram matched CT Detail Coefficients.

(10) Then the fused Detail coefficients will be computed.

(11) Apply Inverse DWT to fused detail coefficients and replaced MRI Approximation Coefficient to get the fused image.

The result of SF-DWT-DCT image fusion technique will produce images with good spatial and spectral quality which will be evaluated in the following section both qualitatively and quantitatively.

VI. Result and Discussions

The CT and MRI datasets we have taken here,

- The 5 CT images
- The 5 MRI images

Under these categories the datasets have been taken.

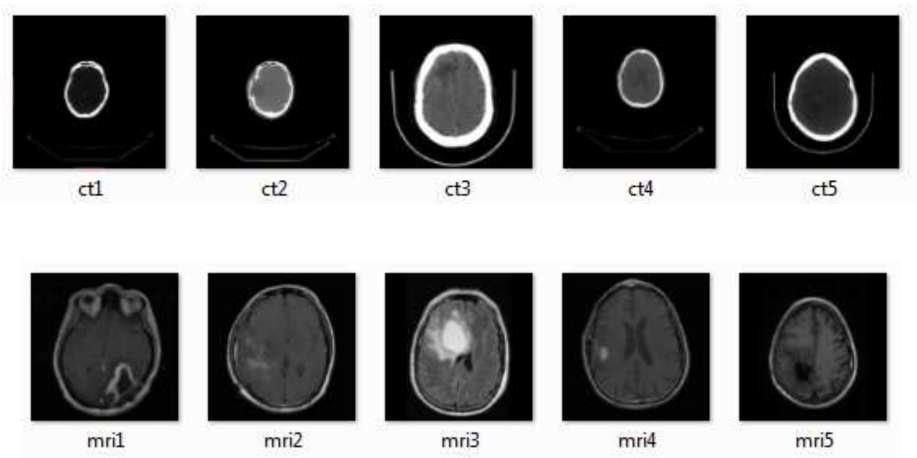
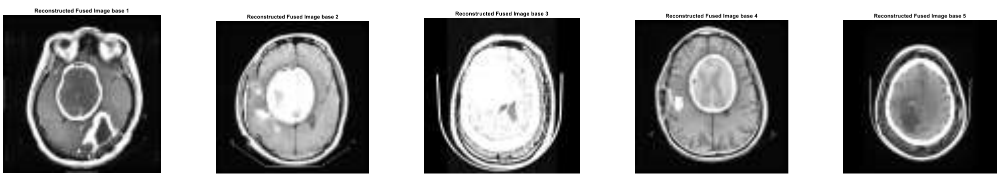


Figure 7: Types of CT and MRI Data Sets

In order to assess the performances of the fusion results of the methods quantitatively, three widely recognized fusion quality metrics are applied in our experiment, which are entropy (EN), mutual information (MI) and structural similarity index metric (SSIM).

Fused images of Base Work: Fused images after applying adaptive structure decomposition (ASD) technique.



Fused images of Wavelet Transform: Fused images after applying DWT technique.

Fused images of Guided Filter: Fused images after applying Guided Filter technique.

Fused images of proposed work: Fused images after applying FS-DWT-DCT technique.

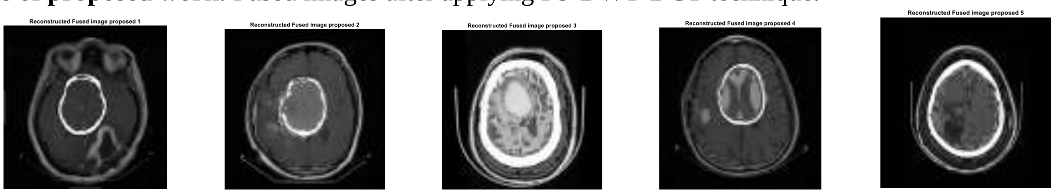


Figure 5.2: Fused output Images

Base image fusion method: Fused images after applying adaptive structure decomposition (ASD) technique.

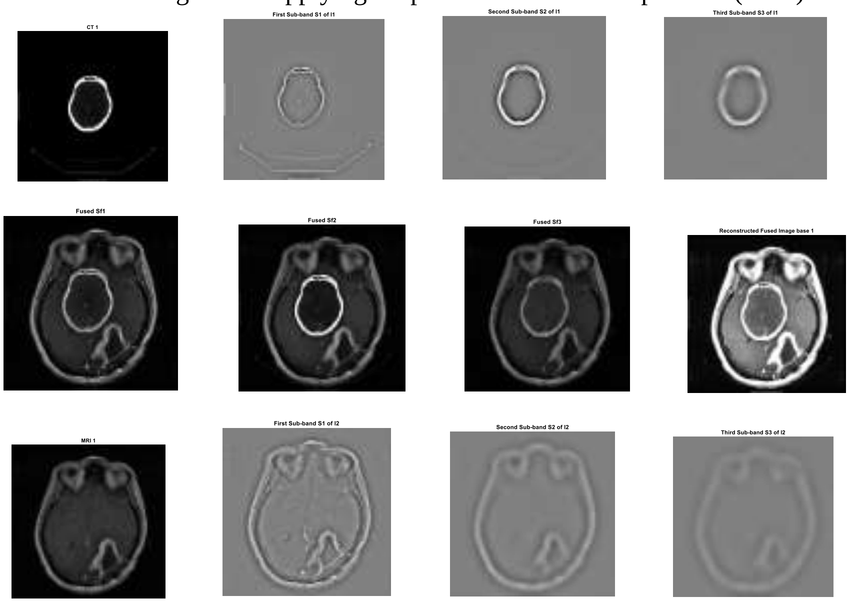
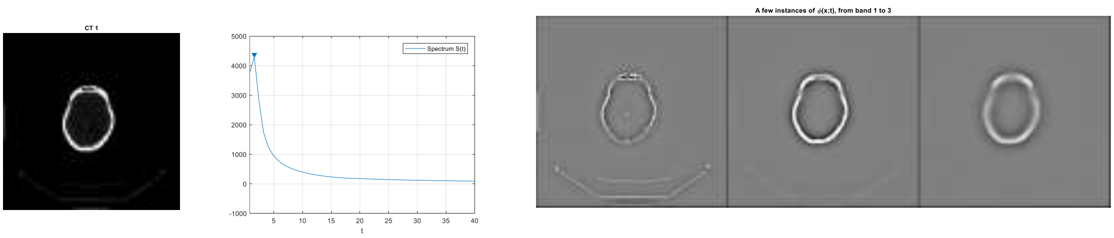
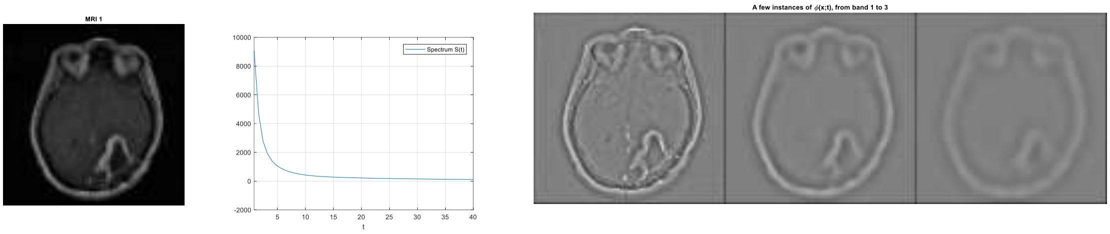


Figure 5.3: Base work Fused output Images

Dividing rule pair: Apply adaptive structure decomposition (ASD) technique.





(a) (b) spectrum (c) first, second and third band

Figure 5.4: Schematic diagram of base dividing rule pair (a) pair of source images (b) spectrum (c) first -third band

SF-WT-DCT based proposed work: Fusion images while applying SF-DWT-DCT proposed technique.

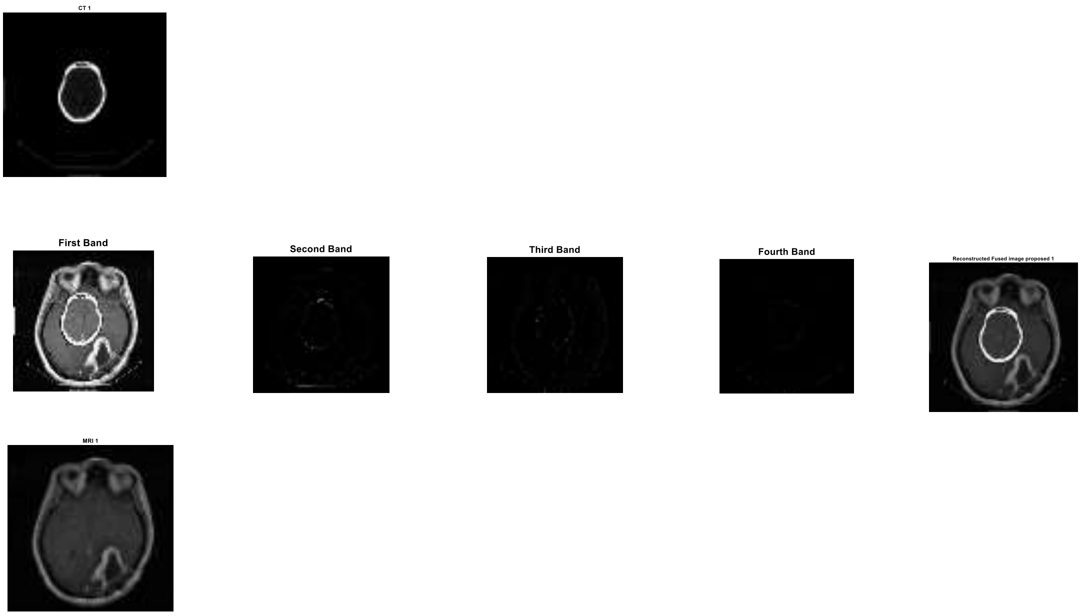


Figure 5.5: Schematic diagram of SF-WT-DCT based proposed work

An effective CT and MR image fusion method via Spatial Frequency Discrete Wavelet Transform with Discrete Cosine Transform is presented. We introduce SF-DWT-DCT into medical image fusion which can extract features in different scale thereby enhancing the interpretability of the sub-bands. We adaptively decompose the images into three sub-bands: sub-bands with small, middle and large scale of issues. Experiments are performed on representative CT and MR images to validate the effectiveness of our fusion method on both subjective and objective assessment.

VII. CONCLUSION

In medical applications, the major issue is how effectively spectral information is preserved while simultaneously improving the spatial information. In order to address this problem, a novel image fusion technique which depends on spatial frequency discrete wavelet transform with discrete cosine transform is developed in this thesis. The proposed technique based on spatial frequency is found to be an improved version of existing standard DWT-DCT image fusion technique. The quality of the proposed technique is analyzed, visually, quantitatively, using reference and non-reference performance indexes. From the experimental analyses, it can be vividly comprehend that the proposed technique has better spectral and spatial quality than standard adaptive structure decomposition (ASD) method.

The results have been evaluated using subjective visual analysis as well as quantitative approaches. To quantitatively evaluate the images, entropy (EN), mutual information (MI) and structural similarity index metric (SSIM) were used. These metrics quantify signal strength, the amount of feature preservation, and recovery of structural features obtained image.

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