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# An Enhanced Multimodal Medical Image Fusion Technique Based on Spatial Frequency Stationary Wavelet Transform

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*Abstract* - **The Image fusion is widely acknowledged as a useful tool for enhancing overall system performance in a variety of application areas such as battlefield surveillance, camouflaged ordnance detection, non-destructive testing defect detection, remote sensing, traffic control, machine learning and health care applications to name few, its own. There are, however, drawbacks to the information gathered from single-modality medical imaging. Medical diagnosis cannot be aided by extensive lesion information from single-modality imaging, which inevitably results in annoyance and poor clinical diagnosis performance. Medical image fusion is a method for resolving this issue; it does so by merging the benefits and supplementary data of several models of source images, eliminating redundant data, and providing a more thorough, accurate lesion description to support specialists in diagnosis and decision-making.**

**Medical image fusion, which merges multi-modal images using image processing, may be useful here. A multiresolution image fusion method uses the Spatial Frequency DCTWT (SFDCT-DWT) technology. In the SF-DCT-DWT technique, the low-resolution MRI image is resampled to the high-resolution CT image, and fusion is performed by injecting the spectral and spatial information from CT and MRI images onto each other using their DCT-DWT coefficients and spatial frequency analysis. These images are from MR and CT imaging. According to experimental data, the recommended strategy surpasses other subjective and objective measures including Entropy (EN), Mutual Information (MI), and Structural Similarity Index Measure (SSIM).**

***Index Terms* - *CT & MRI Image Fusion, SFDWT, ASD, PSNR, SSIM, Spatial frequency etc.***

## I. Introduction

With the technological advancements there has been a considerable increase in the scientific applications in the area of image processing. The type, performance and expertise associated with the image acquisition devices have expanded multifold in the recent decade. Every application area is sensing how images and videos are gradually dominating research and these endow with the directions for the future. Various acquisition mechanisms are being developed, to lead data sensors. Chemical sensors, geological sensors, exploration sensors, remote satellite and medical data sensors are a few of the equipments, emerging to formulate and govern the image acquisition devises. The acquisition devises in the medical domain govern the focus towards improving routine diagnostics. The medical acquisition equipment is used to capture images for diagnosing ailments. The same region, organ or a tissue can be captured from various perceptions and help reveal clinical information, as a whole; vital for diagnosis and treatment planning. With the continuous progression in medical domain, it is achievable to obtain high resolution images with immense clinical aspects at low cost.

In the process, multitude of imaging data is being generated as repeat scans for disease progress or to capture the affected region or lesion by more than one modality. Leading to increased number of computations and higher complexities. There arises a need to combine the acquired raw data from all sources, and to reduce the volume of data without any perceptual loss [1]. Image processing analyzes to disseminate the expanding data. Image fusion is an image processing technique to combines images into a composite image. The combined image must be more informative and should improve the quality in comparison to original images. Fusion thus decreases the amount of unneeded information to be accounted for further processing.

### *A. Image Fusion*

Data fusion was conceptually introduced in 1950‟s. The literature depicts the same meaning for merging, integration, combination, synergy and fusion [2]. "Image fusion is the combination of two or more different images to form a new image by using a certain algorithm". This definition was pioneered by Pohl, Van Genderen (S1994). The data can be sourced from two-dimensional, three-dimensional or higher-dimensional inputs.

The fusion algorithm as defined by [2] must realize the following conditions as to:

- Preserve all significant source information
- Preserve all relevant information,
- Should not introduce artifacts, inconsistencies, noise, distortion
- Should be robust, shift and rotational invariant,
- Be independent of location, orientation, registration errors and
- Possess temporal stability and consistency in case of image sequence fusion;
- Preserve high contrast regions, revealing internal details in a synergistic manner.

In terms of grey level, changes must not be introduces during the fusion. But these grey levels must exist in the fused sequence without delay. When the images differs in size, structure, shape and resolution, the grey levels must exist in the fused sequence without delay but fixations changes must not be introduced as static images are taken into consideration. The generic image fusion is represented in fig 1.

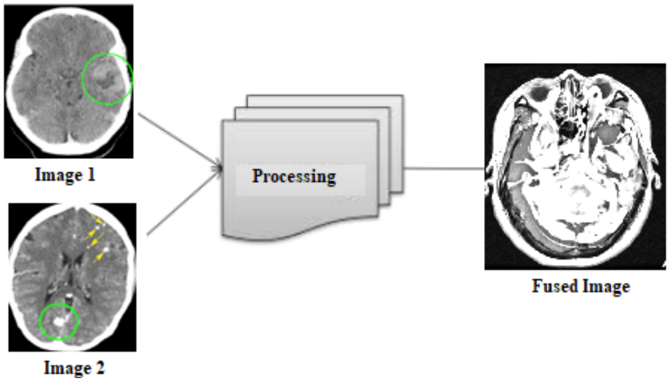


Fig. 1 Generic Fusion Model

The fusion process can be realized either by using hardware based techniques or software based techniques. The hardware based techniques are not only associated with higher levels of complexity but also leads to costly image capturing mechanism. As per the present scenario these machines do not possess means to store and accumulate the computed results. Subsequent processing on the ailment, analysis and re reference needs to start a fresh with ready reference to previous findings [3]. Therefore due this, only limited flexibility within hardware equipments is offered for medical diagnosis. The software based techniques do not have such limitations and are more cost effective. These provide higher level of flexibility to process the input data multiple times without incurring any additional cost. There are issues associated with software based processing as these do not adequately preserve the original diagnostic information. It is challenging to retain the information due to the heterogeneity of input data in the source images.

The objective of fusion is to incorporate data and formulate a new image by coalescing complementary images of different types as multi-sensor, multi-temporal or multi-view images, [4]. Fusion is categorized into different types based on image input as

*1) Multi-view fusion:* It involves fusion of images acquired from different viewpoints. It merges multi-dimensional acquisitions of the same image from diverse perspectives into a harmonizing single fused image from different views. Various universal methods are proposed in literature as pixel wise weighted average, object level fusion etc. In fact, there is lots of distinctive information to be unexploited between two or more images which can enhance classification effect and improve ability of detect changing view point.

*2) Multi-temporal fusion*: It includes images from the identical scenes of same modality taken at different times to perceive alterations between them. This technique defines parameters to fuse realistic images that exploit temporal aspects of image acquisition. It involves multiple images, acquired at different times to reinforce the pragmatic concepts and perceive alterations. Multitemporal remote sensing images classification have attracted more and more attention in the last decade because of a wide range of applications of multitemporal images in long-term environmental monitoring and land cover change detection and increasing multi-temporal data available.

*3) Multi-focus fusion*: Is the process of fusing two or more images of a scene. The general method of multi-focus fusion is to recognize and merge the regions in focus. It works on images obtained with different focal lengths [5]. It encompasses fusion of two or more images of a scene, acquired with varied focus. It aims to recognize and merge the regions to expand the visual details.
Multi-focus image fusion is a multiple image compression technique using input images with different focus depths to make an output image that preserves information. It can be classified into two categories of transform and spatial domains.

*4) Multi-modal fusion*: It combines images obtained from different sensors. These images differ in acquisition principle due to the inherent difference in sensors. This fusion category is mostly dominated in the area of Remote Sensing and Medical processing. Visible and infrared satellite image under remote sensing or anatomical and functional medical modalities are integrated to encompass complimentary information into a fused image. Images acquired using different model equipments are synthesized in medical domain to aid better resolution to possess maximum possible features in the fused image for further processing and analysis.

*5) Multi restoration fusion:* involves the basic idea to remove the degradation from an image. The resultant fused image must be a true part of the source images. The diverse types of degradation are artifacts, additive noise, convolution loss and resolution decimation. This approach can also be extended to aspects pertaining to super resolution fusion, where blurred input images of low spatial resolution are fused to provide with a high resolution image. Sample source images of different image types are illustrated in fig 2.

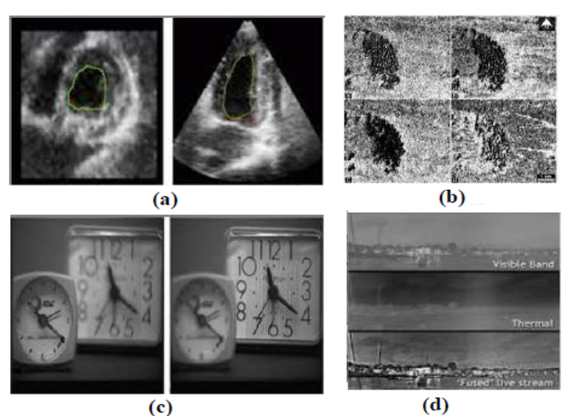


Fig. 2 Fusion Categories (a) Multiview (b) Multi Temporal (c) Multi focus (d) Multimodal fusion

*B. Image Fusion Categorization*

The information attained from each underlying image is partial and incomplete, only a few investigative characteristics are attainable due to complex structure and limited capturing visibility. This leads to multiple diagnostic interpretations, imprecise readings and ambiguous diagnosis. To decipher image fusion methods are broadly categorized in two domains, spatial domain and transform domain [6]. In these domains, numbers of techniques are reported by researchers in literature. Each approach has a limited sphere of influence based on a particular application.

*Spatial Domain:* Medical image fusion combines multiple images to perform positive characterization of diagnostic content. The physical and structural information present in an image is hybrid in nature. The spatial domain techniques comprise of simple combination of images in a linear or non linear manner. Combination mechanism of simple averaging or choose maximum value from the set are administered. In spatial domain the images can be directly combined at pixel level by merging the gray level pixel intensity values, by means of certain combining strategy. These function to represent the pixel intensity value pi at a spatial location (m, n) is given by pi (m, n). The input images are represented as ImA and ImB . The formation of input images are given by equation (1) and equation (2) as

$$Im^A = C_a P^i(m,n).Im^A \quad (1)$$

$$Im^B = C_b P^i(m,n).Im^B \quad (2)$$

The mathematical representation of the averaging fusion technique is given by equation (3) as

$$Im^F(A.B) = (C_a P^i(m,n).Im^A + C_b P^i(m,n).Im^B)/2 \quad (3)$$

Where Ca and Cb are constants defining the fusion mechanism. The combination of images based on selection of the maximum pixel value at each spatial position (m, n) to obtain the fused image is given by equation (4).

$$Im^F = \max\,[P^i(m,n).Im^A, P^i(m,n).Im^B] \quad (4)$$

In spatial domain, the fusion rules are very sensitive to random noise. Minute change in pixel values, drift the fusion results from actual. These variations in the original medical images lead to spatial inconsistencies [7]. Rather than the attained absolute values of intensities, the spatial alignment of image features, order of processing, and neighboring values are more vital to guide the performance and associated misalignment errors. Images from complementary modalities report higher registration errors, posing a limitation in obtaining accurate fusion results.

*Transform Domain:* In medical imaging methods different imaging equipment is used to capture clinical information using anatomical or functional modalities. By acquiring different input images, it is aimed to obtain abundant clinical information with precision. Transform domain techniques are governed by multiscale principle. Prior to fusion the intensity pixel values are altered into the transform domain. In transform domain it is better accustomed to attain the above mentioned precision. The salient image features are depicted with improved clarity. Transform domain techniques are broadly classified into color space transform, karhunen loeve transform and multiscale transforms.

The color space transforms plays an important role when dealing with images from medical domain representing input into color perception. Various techniques have been proposed in fusion based on color space models[8]. In these techniques, medical modality is inserted into one of the color channels for processing. The chemical compositions from the functional modality represent the psychology of the organs and tissues with metabolic changes in pseudo color.

The multiscale transforms represent edges, boundaries and discontinuities analogous to human visual system. These are broadly segregated into pyramid transforms, basic wavelet transforms and advance wavelet transforms, with more detailed information being captured at higher scales. The pyramid techniques in multiscale domain are Laplacian Pyramid, Morphological Pyramid, Filter Subtract Decimate Pyramid, Ratio to Low Pass pyramid, Contrast Pyramid and Gradient Pyramid technique comprise the [9]. Pyramid transforms comprise of series of original images. These transforms are described for multi resolution image analysis. With gradually decreasing resolution the structure performs filtering of the original image. At each level the image is filtered with size and resolution halved from the predecessor in both the spatial directions. This difference is maintained to permit perfect reconstruction. During this phase the image is rebuild by up sampling.

The basic wavelets transforms include Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Lifting Wavelet transform (LWT), Discrete Dyadic Wavelet Transform (DDWT), Dual Tree Complex Wavelet Transform (DTCWT) and Discrete Fractional Wavelet transform (DFRWT). These are extended to complex wavelets as Ripplet Transform (RT), Shearlet Transform (ST), Curvelet Transform (CVT), Contourlet Transform (ConT) and the Non-subsampled Contourlet Transform (NSCT) [10-11]. The advanced wavelets are more complex in terms of time and computational needs. The techniques are enlisted in fig 3.

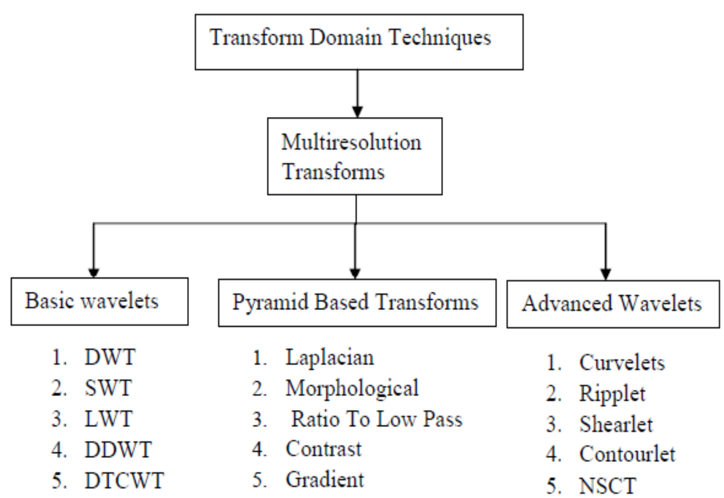


Fig. 3 Multiresolution Transform Domain Fusion Techniques

## II. Literature Review

Medical image fusion combines data acquired from two dimension still images, three dimension video frames or higher dimensions inputs. There are different medical modalities designed to extract appropriate medical information. Each modality extracts limited content from the source modalities. The alliance of source images with respect to diagnostic analysis to establish the fusion principle is challenging. Disease diagnosis and monitoring of the underlying bone, organ or the tissue can well be captured using a radiological modality for clinical evaluations, further classification and processing. The content and structured labeling of the image medical data is acquired from the image scans. Images are represented in terms of features, color, texture, contrast, brightness and other representational parameters. There are different medical modalities in existence, each assisting in a different perspective. The presentation and performance aspects concerning single modal fusion and multi modal fusion are discussed.

Yang et al. implemented the pixel level decomposition on weighted average fusion rule in wavelet domain [12]. 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 [13]. 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 [14]. 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 [15]. 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 Cheng et al. [15]. 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.

Xian hua Zeng, et. al 2019 proposed an algorithm to generate enhanced color medical images with discriminative features [15]. It gives fine details with minimum loss of information for Ultrasound, CT, MRI, DTI, and PET medical modalities. The algorithms are based on hierarchical density peak clustering (CPMI-DPHC) and multifeature fusion. The method generates high dimensional data with intrinsic details of the gray scale images and fusing it with luminance features of the original image. The regional representative pixels then mapped to three dimensional spaces using the manifold learning method and these pixels are converted to the RGB color space. The images with more colors provided more detailed information and had better colorization effect. It was found that the results for Ultrasound images were not credible, while the results obtained for, MRI, CT and PET provided clear text based information and details.

Rabia Bashir, et.al, 2018 critically examines two multi-modal image fusion techniques [17]. These are Stationary Wavelet Transform (SWT) and Principal Components Analysis (PCA) technique to determine the efficiency of one technique over the other. The two fusion techniques are applied on multi-modal pre-aligned, predimensioned and registered Satellite images, Visible and infrared images, CT and MRI images, X-ray and MRI images and stereo images. The quality of fused image obtained is assessed. Based on these metrics, it was found that the PCA technique showed better, results for fusion of satellite images, X-Ray and MRI images and stereo images while SWT gave better performance for CT/MRI and Visible/Infrared images.

## III. Proposed Algorithm

In Image processing, fusion of MRI image and CT image is an important technique. This paper incorporates a multiresolution image fusion algorithm based on the proposed Spatial Frequency SWT-DCT (SFSWT-DCT – Spatial Frequency Stationary Wavelet Transform with Discrete Cosine Transform) technique. In SF-SWT-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 SWT-DCT coefficients by evaluating the spatial frequency (SF – Spatial Frequency).

*Spatial Frequency SWT-DCT (SF-SWT-DCT) Image Fusion Method*

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 [18]. 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 SFSWT 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.

The abrupt singularities and modifications are well taken care of in DWT. But the transform is not shift dependent which makes it difficult to preserve segment information. Pseudo Gibbs effect, artefacts and lost edge information in wavelets lead to poor results with medical images. To overcome the limitations posed by DWT, a member of wavelet family, Stationary Wavelet Transform (SWT) is preferred.

*Stationary Wavelet Transform*

Stationary wavelet is also called undecimated wavelet transform. It is a spectral wavelet transform with superior localization and time invariance. Stationary wavelet have improved phase information. Down sampling and up-sampling is suppressed in forward transform and inverse transform respectively. To better preserve the detail components, SWT is applied at each point and zeros are inserted between filter taps to up-sample at every decomposition level. The number of pixels remain same at every level, notably ensuring abrupt changes and making it a redundant transform [19]. The SWT can only be defined for signal length divisible by 2L. The maximum permissible decomposition level is given by L. It better preserves the original signal, time information and localization at every level. SWT with the no decimation principle, invariance and orthogonal directionality, SWT gives superior results and better preserve the detail coefficients. It in turn results in higher complexity, redundancy and extends poor response to image feature directionality**.** In SWT, a low pass filter is represented by $L_{PF}^{i}$ and high pass filter by $H_{PF}^{i}$, where i is the level of decomposition. The filters at each level are represented as

$$L_{PF}^{i}(i+1) = \uparrow 2(L_{PF}^{i})\ and \qquad (5)$$
$$H_{PF}^{i}(i+1) = \uparrow 2(H_{PF}^{i}) \qquad (6)$$

The block diagram of SWT decomposition mechanism is depicted in figure 4 below extracting coefficients at three levels:

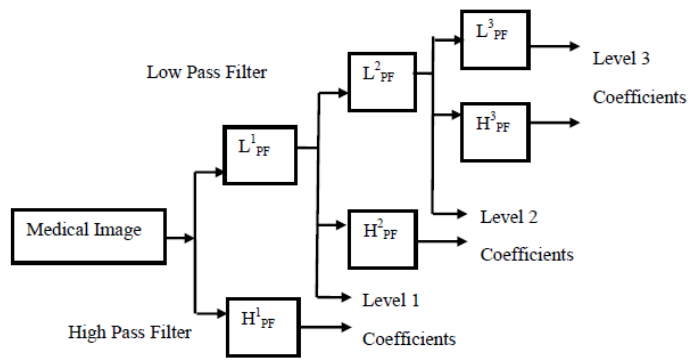


Fig. 4 Stationary Wavelet Decomposition Components

Stationary wavelet transform is applied on a 2 dimensional image to decompose and obtain the approximation coefficients using scaling function (φ) and detail coefficients using the wavelet function (ψ) at each level. The scaling function φ(t) is given by equation below:

$$\varphi(t) = \sqrt{2}\sum_{m} h0(m)\varphi(2t-m) \qquad (7)$$

and wavelet function is

$$\psi_j(t) = \sqrt{2}\sum_{m} hi(m)\varphi(2t-m), j = 1,2 \qquad (8)$$

The decomposition for SWT at level J+1 for approximation A and detail image coefficients { H, V, D} are given as follows:

$$I_m A_{j+1,a1,a2} = \sum b1 \sum b2\, L_j^{\uparrow 2j}(b1-2a1) L_0^{\uparrow 2j}(b2-2a2) I_m A_{j,a1,a2} \qquad (9)$$
$$I_m H_{j+1,a1,a2} = \sum b1 \sum b2\, L_j^{\uparrow 2j}(b1-2a1) L_0^{\uparrow 2j}(b2-2a2) I_m H_{j,a1,a2} \qquad (10)$$
$$I_m V_{j+1,a1,a2} = \sum b1 \sum b2\, H_j^{\uparrow 2j}(b1-2a1) H_0^{\uparrow 2j}(b2-2a2) I_m V_{j,a1,a2} \qquad (11)$$
$$I_m D_{j+1,a1,a2} = \sum b1 \sum b2\, H_j^{\uparrow 2j}(b1-2a1) H_0^{\uparrow 2j}(b2-2a2) I_m D_{j,a1,a2} \qquad (12)$$

As diagnostic information is vital, SWT well preserves the detailed information with better computational complexity than most transform domain techniques including NSCT [20].

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 SWT to MRI image and calculate the approximation and detail coefficients.

(3) Similarly apply SWT 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.

(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.

(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-SWT-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.

## IV. Result and Discussions

We have taken the CT and MRI datasets as follows,

- The 5 CT images
- The 5 MRI images

The datasets have been taken under these categories (Fig 5). Fusion must provide superior image with minimum artifacts and deflection of source information. The detailed description of the proposed fusion scheme is illustrated in above. The input image set is fed to Stationary Wavelet Transform (SWT) for decomposition. The images are decomposed into approximation and detail components, formulating the feature map. Under activity level measure dissimilar fusion rules and select maximum are adopted for approximation and detail subband components respectively. Inverse Stationary wavelet transform is applied to obtain the final fused image. Each modality endow with precise insight into an organ, lesions or functionality [21]. Based on the organ under study, the strength of each modality is exploited.

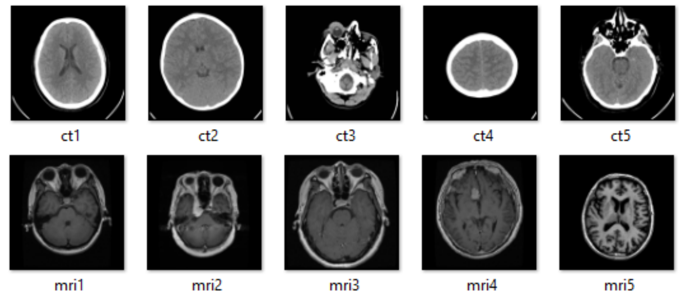


Fig. 5 CT and MRI Data Sets

When functional modality like PET or SPECT is combined with anatomical MRI or CT, the strengths of both the modality sets are exploited to provide improved anatomical localization of physiological processes. It is hard to accomplish the entire diagnostic facts from one image modality. Capturing all diagnostic characteristic by one perspective may mislead the diagnostic analysis to authentically reveal the underlying tissue. Table 1 depicted the various parameters for 3 techniques used GFF, WT, and SFDCTSWT.

TABLE I Multi Modal Image Fusion Results

| **MULTIMODAL IMAGE FUSION** | | | | | |
|---|---|---|---|---|---|
| **Technique** | **Entropy** | **MI** | **MSE** | **PSNR** | **SSIM** |
| GFF | 4.3842 | 8.2442 | 0.46917 | 3.4484 | 0.47977 |
| WT | 5.4063 | 8.2731 | 0.052977 | 13.399 | 0.60433 |
| SFDCTSWT | **5.6474** | **8.3194** | **0.021624** | **16.731** | **0.75855** |
| | | | | | |

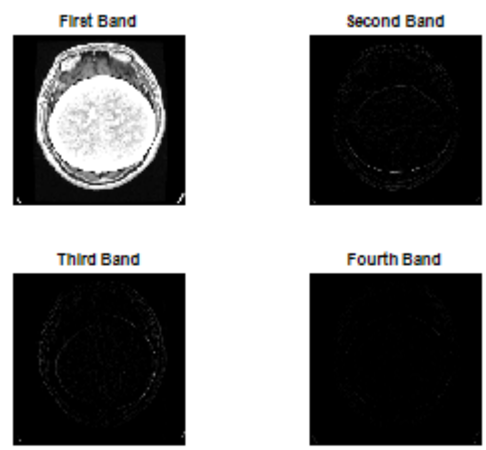


Fig. 6 Schematic diagram of sub band

Fig 6 shows the four sub bands of a single image, after applying the SF-DCT-SWT technique using HAAR wavelet function. By applying the technique, the low resolution input image is decomposed into four sub-bands, three high frequency sub-bands (LH, HL and HH) and the other one low frequency sub-band (LL) which is a low resolution approximation of the input image but all the four sub-bands obtained are of half the size of that of the input image. These sub-bands are shown in the Fig. 6.


Fig. 8 Reconstructed Fused Image

After applying the inverse transform, the reconstructed fused image. In the reconstruction step, we use the inverse of the transform to combine the fused low- and high-frequency coefficients and to produce the fused image. The algorithm discusses the steps of the proposed fusion method for multi-modality medical source images.

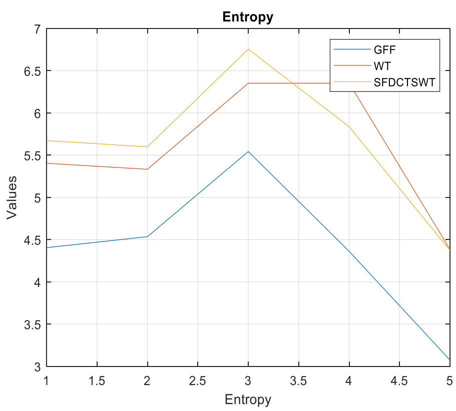


Fig. 9 Graphical Representation of Entropy with recent proposed method

Image information entropy is one of the important factors that determine the final effect of image fusion. The larger the information entropy, the more detailed information contained in the experimental result graph; On the contrary, the smaller the information entropy, the less detailed information contained in the experimental result graph. The evaluation results are shown in Fig 9 and Table 1.

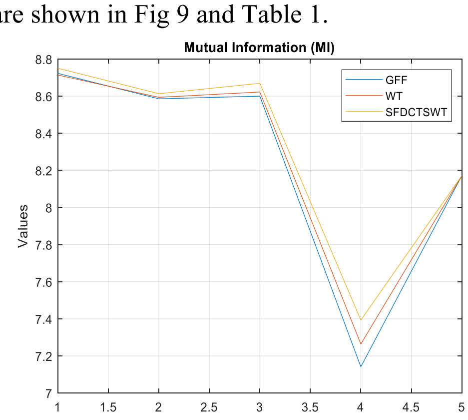


Fig. 10 Graphical Representation of Mutual Information (MI) with recent proposed method

In image fusion assessment, the mutual information for representing the amount of information that is transferred from the source images to the final fused image. The overall fusion performance is the sum of mutual information between each source image and the final fused image, as shown in Fig 10. In this approach only the common information between each of the source images and the fused image is considered whereas no attention has been paid to the overlapping information of the source images. The proposed method have better MI value.

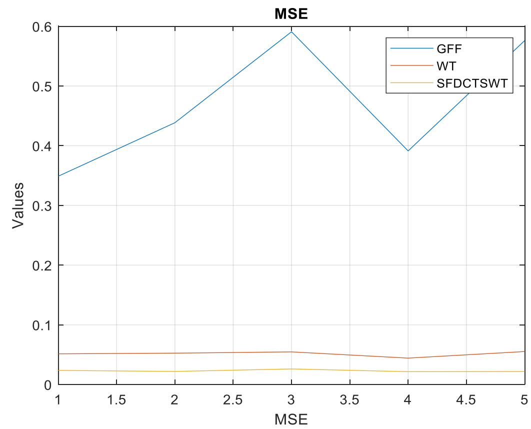


Fig. 10 Graphical Representation of Mean Square Error (MSE) with recent proposed method

Compared with the measured value, the fusion result can not be seen directly, so the mean squared error (MSE) between each measurement result and the is calculated. The MSE results in Fig 10 indicate that the accuracy of the target position after fusion is improved compared to a single image, and the error of the result after fusion is the smallest. We can see the proposed method has minimum MSE.

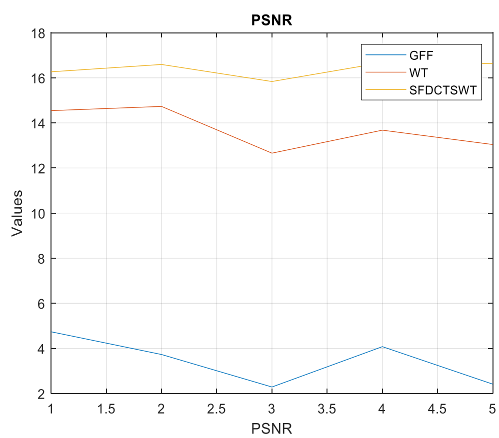


Fig. 11 Graphical Representation of Peak signal-to-noise ratio (PSNR) with recent proposed method

The Peak Signal to Noise Ratio (PSNR) is used for measurement of quality between the two images such as original and a reconstructed image. By measuring the quality of reconstructed image has higher using PSNR. To compute the PSNR, first we have to compute the mean squared error

(MSE). It can be seen that the proposed method has maximum PSNR value, as shown in Fig 11.

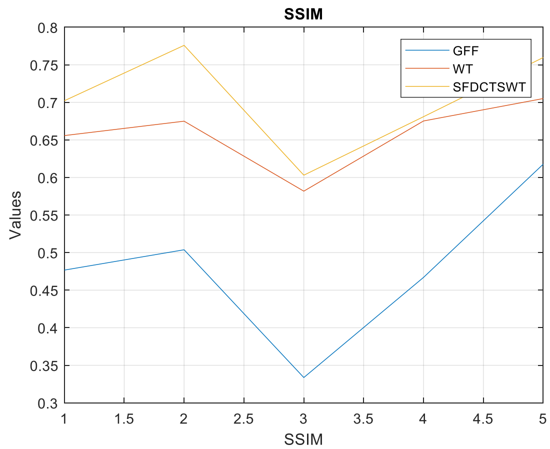


Fig. 12 Graphical Representation of Structural similarity index measure (SSIM) with recent proposed method

The SSIM is a factor that measures the structural similarity between the source image and the fused image. SSIM values between 0 and 1 and higher SSIM values indicate a higher structural similarity between the two images. The final experimental result is presented in Fig. 12. We compare the image quality of images processed. As can be seen from this figure, when the fusion weight ratio is 0.5, the average SSIM value of the final image is the largest, 0.7854. It demonstrates that the final image enhancement effect is best when the fusion weight ratio is 0.5.

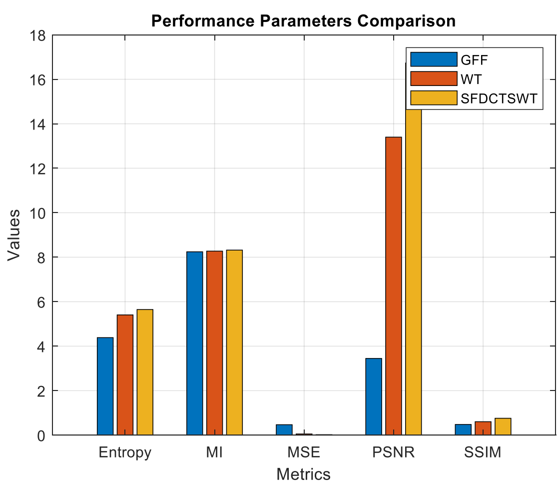


Fig. 13 Performance parameters Comparision

The Fig 12 have thus represented comparison of fusion performances based on Entropy, MI, MSE, PSNR, and SSIM assessment. For average of quality metrics taken on two datasets, it is observed that proposed method provides overall improved results than that of other methods. Also, SFDCT-DWT mostly has outperformed GFF, and WT. Finally, a comparison of time taken by image fusion algorithms to generate high resolution resultant image is plotted in Fig. 13. SFDCT-DWT fusion algorithm proves computationally efficient than others.

## V. 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 stationary wavelet transform with discrete cosine transform is developed. The proposed technique based on spatial frequency is found to be an improved version of existing standard SWT-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. The results have been evaluated using subjective visual analysis as well as quantitative approaches. To quantitatively evaluate the images, entropy (EN), mutual information (MI), Mean Square Error (MSE), Peak signal-to-noise ratio (PSNR) 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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