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A MULTI-RESOLUTION TECHNIQUE FOR THE IMAGE FUSION OF DISSIMILAR MODALITIES OF MEDICAL IMAGES USING MODIFIED DFB

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ABSTRACT

This paper presents an innovative multi-scale technique for fusing two dissimilar modalities of medical images. Image fusion is the process of combining two images to form a single image. The new image will be more informative than these two input images. The two dissimilar modalities are CT and MRI medical images. CT image provides better information about denser tissue and it is not good for soft tissues. MRI image provides better information about the blood vessels, brain, heart, spinal cord and other internal organs and it is less accurate for bones. These two images are fused into a new image to improve the information content for diagnosis. Varieties of algorithms such as Discrete Wavelet Transform, Pyramid Wavelet Transform, Stationary Wavelet Transform, Curvelet Transform and Contourlet Transform are available to fuse two images. This paper proposes an Innovative Contourlet Transform. The fusion rule, Select-Maximum is used. The work is implemented using MATLAB. The results are compared with the existing techniques by using various performance measures such as Image Quality Index (IQI), Mutual Information (MI), Fusion Index (FI),Fusion Symmetry (FS), Fusion Factor (FF), Standard Deviation (SD), Entropy (EN), Root Mean Square Error(RMSE), Peak Signal to Noise Ratio (PSNR).

KEYWORDS: *Modality, CT, MRI, fusion, Multi-scale, DWT, SPW, SWT, Curvelet, Contourlet.*

1. INTRODUCTION

A digital image is a representation of a two- dimensional image as a finite set of digital values, called picture elements or pixels.The field of digital image processing refers to processing digital images by means of a digital computer.Digital image processing focuses on two major tasks,

- Improvement of pictorial information for human interpretation.
- Processing of image data for storage, transmission and representation for autonomous machine perception.

Digital image processing begins to be used in medical applications.Medical imaging is the technique and 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 disease. Noise, artifacts and weak contrast are the principal causes of poor image quality and make the interpretation of medical images very difficult. Poor image quality leads to problematic and unreliable feature extraction, analysis and recognition in medical applications. To improve the image quality many image processing techniques are available. In this paper various image fusion techniques are discussed and an innovative technique is proposed.

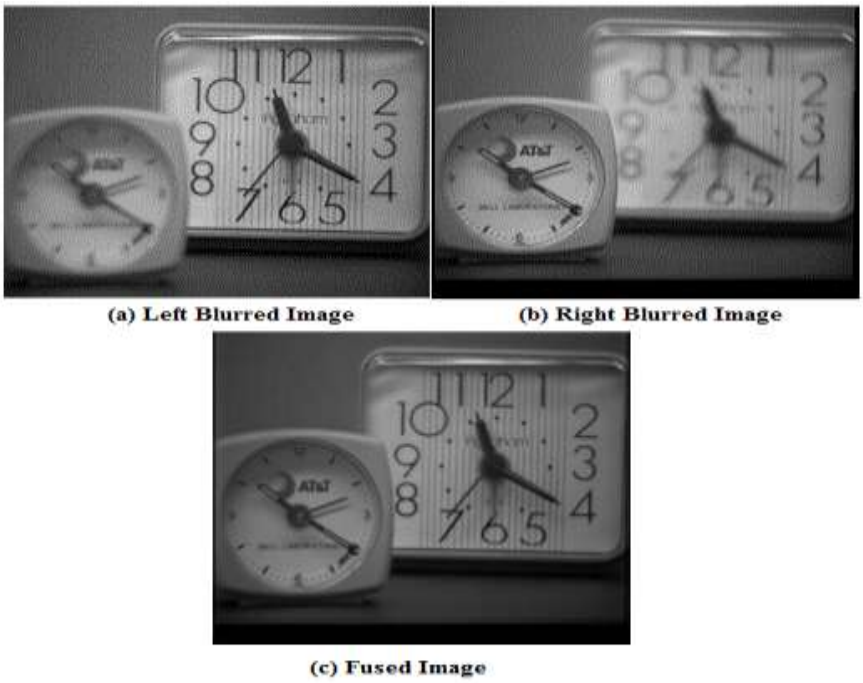


Figure 1: Example of Fused Image.

Image fusion can be defined as the process of extracting the appropriate information from a set of images and then combining them intelligently to form a singlecomposite image with extended information content in order to overcome the limitationof the type and resolution of the hardware sensors capturing images [Zhang 1999]. Imagefusion technology can be applied to many areas dealing with images such as medicalimage analysis, remote sensing, military surveillance, etc. The following figure showsthe example of image fusion.

In Figure 1, each image (a) and (b) has some blurred part due to bad focus. Image (c) is the result of combining the two images using image fusion technology.

1.1 Related Work

The image fusion methods can be broadly classified into two groups - spatial domain fusion and transform domain fusion. The following figure-2 shows the categories of image fusion methods.

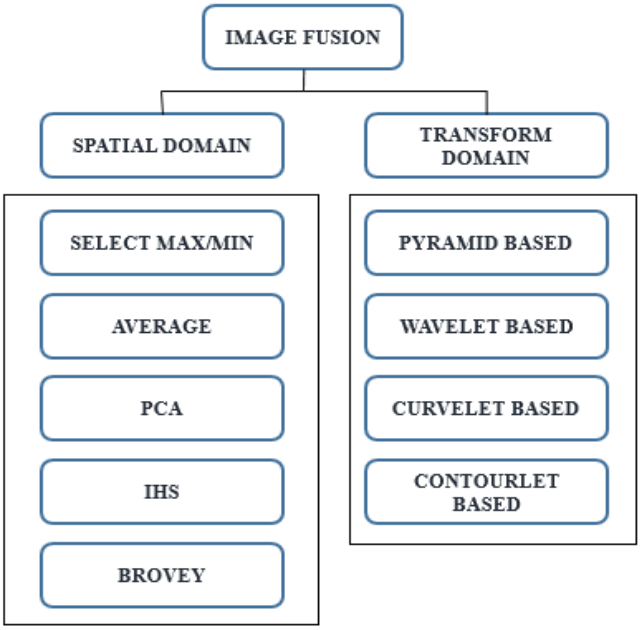


Figure 2: Categories of Image Fusion Methods.

The spatial domain fusion approaches include averaging method, select maximum/minimum method, Brovey method, Principal Component Analysis (PCA), Intensity-Hue Saturation (IHS) based methods and high pass filtering based techniques. The disadvantage of spatial domain approaches is that, they produce spatial distortions in the fused image.The spatial distortions are well handled by transform domain approaches such as Laplacian pyramid based transform, Discrete wavelet based transform, Curvelet based transform and Contourlet

based transform etc. Image Fusion techniques range from the simplest method of pixel averaging to more sophisticated methods such as multi-resolution based fusion. In recent years, multi-resolution transforms have been recognized as a very useful approach to analyze the information content of images for the purpose of image fusion. In this paper, transform domain methods are analyzed in detail and an innovative contourlet based transform method is proposed.

The Discrete Wavelet Transform (DWT) was successfully employed in the field of image processing with the introduction of Mallat's algorithm. Singh et al.(2013) has analyzed a multiscale fusion of multimodal medical images in wavelet domain. Fusion of medical images has been performed at multiple scales varying from minimum to maximum level using maximum selection rule which provides more flexibility and choice to select the relevant fused images. The higher the scale is the more the detailed information is captured from source images to fused image. Since medical images are of poor contrast, more detailed and relevant information should be preserved. Thus, by varying scale, we have flexibility to select appropriate fused image for further operations.

Yang et al. (2010) proposed a novel wavelet-based approach for medical image fusion. After the medical images to be fused are decomposed by the wavelet transform, different-fusion schemes for combining the coefficients are proposed: coefficients in low-frequency band are selected with a visibility-based scheme, and coefficients in high-frequency bands are selected with a variance based method. To overcome the presence of noise and guarantee the homogeneity of the fused image, all the coefficients are subsequently performed by a window-based consistency verification process. The fused image is finally constructed by the inverse wavelet transform with all composite coefficients.

Zaveri et al. (2011) proposed a novel region based multimodality image fusion methodbased on discrete wavelet transform using high boost filtering. This algorithm allows to achieve an accurate segmentation for region based fusion using graph based normalized cut algorithm. The resultant segmented image produced using this framework is used for extracting the regions from the input registered source images which are further processed to fuse different regions using different fusion rules.

Chiorean et al. (2009) have implemented a dedicated application for image fusion using DWT. The application uses Java technologyto integrate it into a distributed process so that the application will be able to be accessed in a remote mode by physicians.

The Stationary Wavelet Transform (SWT) was introduced in 1996 to make the wavelet decomposition time invariant. Stationary Wavelet Transform (SWT) is similar to Discrete Wavelet Transform (DWT) but the only process of down-sampling is suppressed that means the SWT is translation-invariant. The 2D Stationary Wavelet Transform is based on the idea of no decimation. It uses the DWT and eliminates both down sampling in forward transform and up sampling in inverse transform. More specifically, it applies the transform at each point of the input image and saves the detail coefficients and then uses the low frequency information at each level. But SWT transform has poor ability to express the long edges and the curve in image. Zhou (2012) combined the two kinds of transformations like SWT and Curvelet for multi-sensor image fusion, it has good property of herein before methods and can improve the quality of fused images.

The Curvelet transform (CVT) is a multi-scale transform proposed by Candes and Donoho. The Curvelet transform is suited for objects which are smooth away from discontinuities across curves. Fourier Transform does not handle point's discontinuities well because a discontinuity point affects all the Fourier Coefficients in the domain. Moreover, Wavelet transform handles point discontinuities well and doesn't handle curve discontinuities well. Curvelet transform handles curve discontinuities well as they are designed to handle curves using only a small number of coefficients. Anand et al. (2012) implemented algorithm for fusing two different modality medical images based on the Multi- Wavelet Transform (MWT) and Curvelet transform using different fusion techniques and the results are analyzed using different quantitative measures. The images obtained from different medical imaging techniques such as Computer Tomography (CT) and Magnetic Resonance (MRI) images are fused into a new image to improve the information content for diagnosis.

Liu et al. proposed Steerable Pyramid Wavelet Transform and his work was based on his colleague’s Simoncelli and Freeman, Simoncelli et al. (1992) and Freeman and Adelson, work. Prakash et al. (2014) has proposed a steerable pyramid wavelet transform. Unlike most discrete wavelet transforms, the steerable pyramid wavelet transformis a linear multi-scale, multi- orientation image decomposition method, which is non-orthogonal and over complete. The decomposition of input image is performed resulting in low pass subband and high pass

sub band using steerable filters. The steerable pyramid representation is translation and rotation invariant. The primary drawback is that the representation is over complete by a factor of 4k/3, where k is the number of orientation bands.

Contourlet Transform (CT), introduced by Do and Vetterli, starts with a discrete- domain construction. This transform is more suitable for constructing multi-resolution and multi-directional expansions using non-separable Pyramid Directional Filter Banks (PDFB) with small redundancy factor. It decomposes images at different scale to several components, which account for important salient features of images. Therefore, it enables a better performance than those performed in the spatial domain.

1.2 Motivation and Justification of the Proposed Work

Motivation for image fusion is the result of recent advancements in the medical imaging field. As the new image sensors are of high resolution and are available at low cost, multiple sensors are used in a wide range of imaging applications. These sensors are of high spatial and spectral resolution and offer faster scan rates. 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, medical imagingsystemswere benefited by these multi-sensors. As the number of sensors increase in an application, the more proportionate amount of image data is collected. To improve imaging system's performance, deployment of additional sensors is permitted by a corresponding increase in the processing power of the system. A sensor grabs multiple images of a location and one of them will be considered for analysis. However, the considered image may not have good spatial and spectral resolution. To overcome this and to generate a fused image with high spatial and spectral resolution, this paper identifies the need for image fusion by developing new methods to improve the performance of existing fusion methods.

The most essential dispute concerning image fusion is to decide how to merge the medical images. In recent years, a number of image fusion methods have been projected. One of the primitive fusion schemes is pixel-by-pixel gray level average of the source images. This simplistic method often has severe side effects such as dropping the contrast. Some more refined approaches began to develop with the launching of pyramid transform in mid-80s. Improved results were obtained with image fusion, performed in the transform domain.

The pyramid transform solves this purpose in the transformed domain. The basic idea is to perform a multi-resolution decomposition on each source image, then integrate all these decompositions to develop a composite depiction and finally reconstruct the fused image by performing an inverse multi-resolution transform. A number of pyramidal decomposition techniques have been developed for image fusion, such as, Laplacian Pyramid, Ratio-of-low-pass Pyramid, Morphological Pyramid, and Gradient Pyramid.

Most recently, with the evolutionof wavelet based multi resolution analysis concepts, the multi-scale wavelet decomposition has begun to take the place of pyramid decomposition for image fusion. Actually, the wavelet transform can be considered one special type of pyramiddecompositions. It retains most of the advantages for image fusion but has much more complete theoretical support.The Discrete Wavelet Transform primarily suffers from the various problems (Ivan et al (2005) such as oscillations, aliasing, shift variance and lack of directionality.

The ringing artefacts introduced by DWT are also completely eliminated by the implementation of contourlet transform based image fusion methods.The proposed innovative contourlet transform based fusion method in this paper also exhibit improvement with respect to objective as well as subjective evaluation point of view as compared to some of the existing image fusion techniques.

1.3 Outline of the Work

Image processing techniques primarily focus upon enhancing the quality of an image or a set of images and to derive the maximum information from them. Image Fusion is such a technique of producing a superior quality image from a set of available images. It is the process of combiningrelevant information from two or more images into a single image wherein the resulting image will be more informative and complete than any of the input images.

The two images from different image modalities are shown Figure 3. The first image is a Computed Tomography (CT) that shows

the hard structure of the body such as skeleton or bone. The second image is a Magnetic Resonance Imaging (MRI) that shows the soft tissue of body. Each image has its own limitation, which can be solved by creating the fused image from two different image

modalities. This would lead to improved diagnosis, better surgical planning, more accurate radiation therapy and countless other medical benefits.

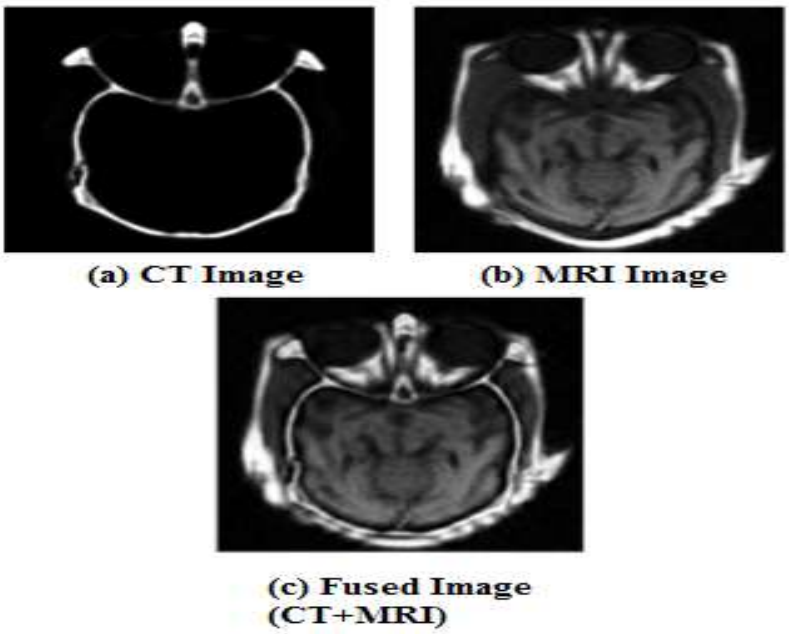


Figure 3: Sample Input and Output Images.

In this paper, various existing transform based image fusion methods like DWT, SWT, curvelet and contourlet transform are analyzed. Finally an innovative contourlet transform method is proposed to fuse two multi-modality medical images. CT and MRI images are get fused in this work. Contourlet transform is a multi-resolution analysis of images. Usually, in this method, the Laplacian pyramid (LP) is first used to decompose the input image so that it can capture the point discontinuities.Secondly, a Directional Filter Bank (DFB) is used for filtering purpose so that it can link point discontinuities into contour segments by considering four neighboring pixels (Kumar et al.(2014). In the proposed method, eight neighboring pixels are considered to improve the quality of fused image. Then the transformed image is fused by applying the fusion rule, Select Maximum. Finally, Inverse transform is applied to get fused image. This process is illustrated in the following figure 4.

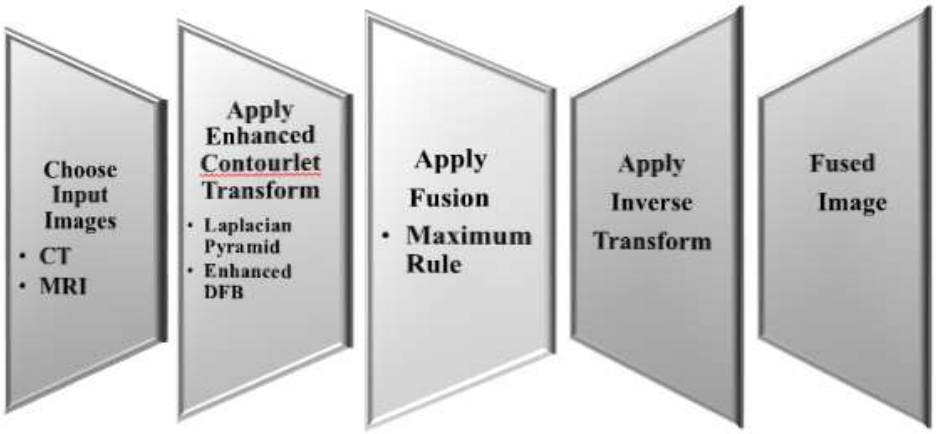


Figure 4: Innovative Contourlet Based Fusion Method.

1.4 Organization of the Paper

Including the introduction, the paper is divided into five sections. The organization of the paper is presented below.

Section-2 Methodology:This chapter is devoted to the complete methodology and illustration of an innovative contourlet based image fusion.

Section-3 Experimental Design and Result: The method has been implemented in MATLAB and tested for various CT and MRI images. The design and the output is explained in this chapter.

Section – 4 Performance of Evaluation: The quality of fused image is evaluated using various performance measures. The values of various existing fusion methods and the proposed method is compared and analyzed with the help of tables and graphs.

Section – 5 Conclusion: The overall conclusion of the paper is presented in this chapter.

2. METHODOLOGY

Contourlet transform is a multi-resolutionanalysis of images. Usually, in this method, theLaplacian Pyramid (LP) is first used to decompose the input image so that it can capture the point discontinuities.Secondly, a Directional Filter Bank (DFB) is used for filtering purpose so that it can link point discontinuities into contour segments (Kumar, Rajesh 2014).

The Laplacian pyramid was first introduced as a model for binocular fusion in human stereo vision by Burt and Adelson, where the implementation used a Laplacian pyramid and a maximum selection rule at each point of the pyramid transform. Essentially, the procedure involves a set of band-pass copies of an image is referred to as the Laplacian pyramid due to its similarity to a Laplacian operator. Each level of the Laplacian pyramid is recursively

constructed from its lower level by applying the following four basic steps: blurring (low-pass filtering); sub-sampling (reduce size); interpolation (expand); and differencing (to subtract two images pixel by pixel). In the Laplacian pyramid, the lowest level of the pyramid is constructed from the original image.

In the DFB method only four neighborhood pixels are considered to form the contours. Since the pixels from top, bottom, left and right are considered, some contours may be missing. This concept is illustrated in Figure 5.

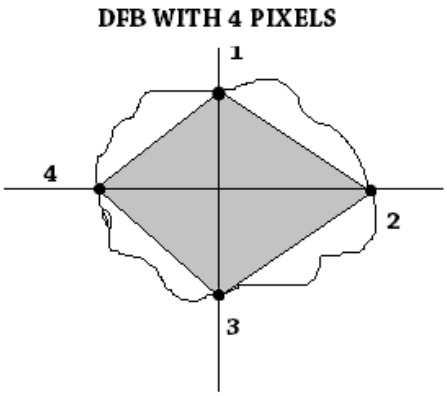


Figure 5: Selecting Contour with Directional Filter Bank (DFB)

To overcome the above said problem, an innovative DFB method is proposed in this paper. In this enhanced method, eight neighborhood pixels are selected to form contours, so that there is no chance of missing any contour. This concept is explained in Figure6.

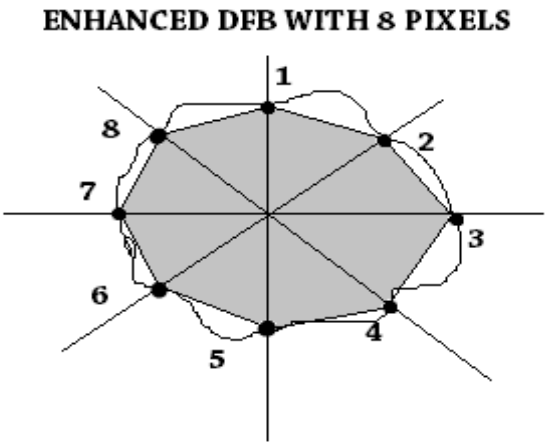


Figure 6: Selecting Contour with Enhanced Directional Filter Bank (DFB).

The algorithm for fusing images using the enhanced Contourlet Transform is explained as follows.

1. The two images,i.e CT and MRI are taken as Input images

2. Each Input Image is then analyzed and decomposed using Laplacian Pyramid method

- Decomposition: In this stage, the registered two input images (A, B) are decomposed (LL, LH, HL, HH) with efficient double filter bank scheme such as Laplacian Pyramid (LP) and Directional Filter Bank (DFB). Laplacian pyramid used to derive the edge point. Directional filter bank is used to connect the discontinuities point in linear structure.
- Then the enhanced Directional Filter Bank method is applied to select contour by considering EIGHT neighborhood pixels.

3. Fusion Rule is applied to the above said decomposed image.

- Lowpass subband fusion: The lowpass subband coefficients are approximation of the source images. Local energy based combination of two distinct modes (selection mode, average mode) used to calculate the final fused coefficient. First local energy E(x,y) is calculated by centering the current coefficient in the approximate subband L.[7] Then the salience factor (MABj) calculated to determine whether the selection mode or average mode used to fuse the approximation coefficient. Then the salient factor compared to a predefined threshold t. If salient factor greater than the threshold (MABj(x,y) > t) on this condition, average mode applied. For condition MABj(x,y) <= t selection mode used.
- Highpass subband fusion: The highpass subbands are fused using maximum selection method. The maximum selection is defined as

$$T_{i,j}^{F}(x,y) = \max(d_{i,j}^{A}(x,y) + d_{i,j}^{B}(x,y))$$

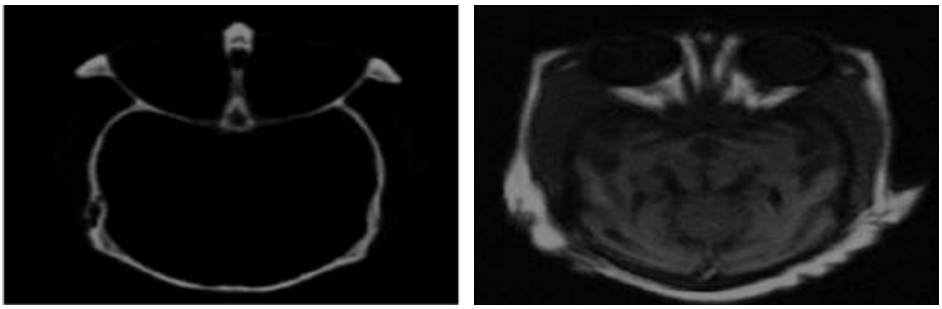
Wherei (=LH, HL, HH) denotes the subbands, j is block number, di,j is highpasssubband block image and Ti,jF is highpasssubband coefficient fused image. Select-Maximum fusion rule is used for the fusion of the Contourlet coefficients.

4. Reconstruction of fusion image: To derive fused image from the fused lowpass subband coefficient and highpass subband coefficient applied inverse contourlet transform.

3. EXPERIMENTAL DESIGN AND RESULT

The proposed method is implemented in MATLAB. In this work, the two different modalities CT and MRI of medical images are taken as the source images. The CT image in Figure 7 (a)

shows the bone information and the MRI image in Fig.7 (b) displays the soft tissues information. Both input images are two dimensional of size 256X256.Discrete Wavelet, Stationary Wavelet, Steerable Pyramid Wavelet, Curvelet, Contourlet and the proposed Innovative Contourlet Transform are applied on the source images and then transform coefficients obtained are fused using Select-Maximum fusion rule.



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

The corresponding outputs are shown in the Figure7(c), (d), (e), (f), (g), (h)

The fused images based on various multiresolution techniques and the proposed technique are as follows.

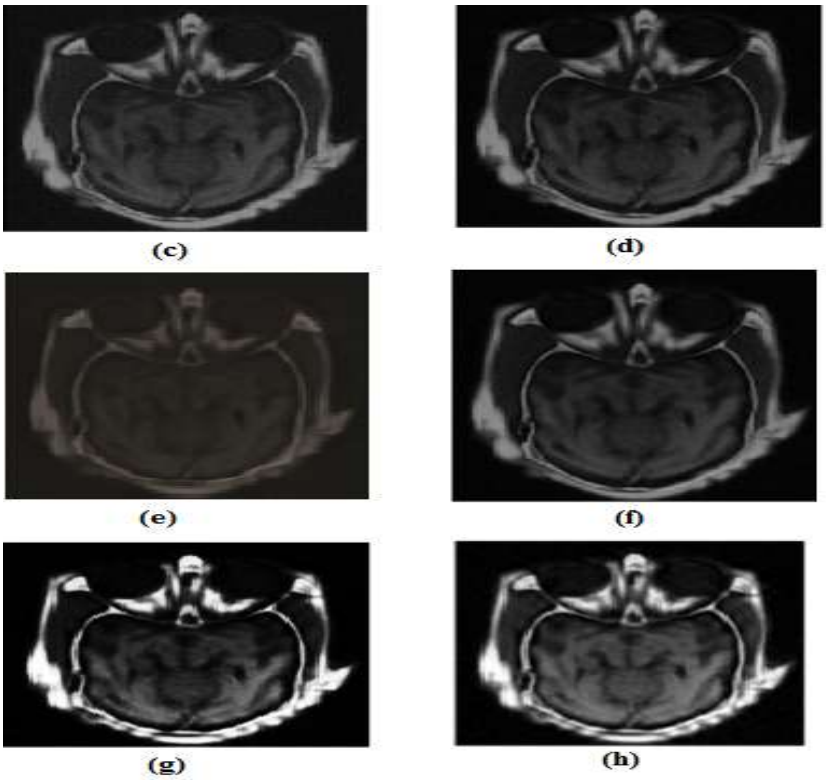


Figure 7: (a) Input Images-CT (b) MRI (c) Fused Image by DWT (d) Fused Image by SWT (e)Fused Image by SPT (f) Fused Image by Curvelet (g) Fused Image by Contourlet (h)Fused Image by Proposed Method.

4. PERFORMANCE OF EVALUATION

The general requirement of an image fusing process is to preserve all valid and useful information from the source images, while at the same time it should not introduce any distortion in resultant fused image. Performance measures are used essential to measure the possible benefits of fusion and also used to compare results obtained with different algorithms.

4.1 Metrics

Evaluation measures are used to evaluate the quality of the fused image. The fused images are evaluated, taking the following parameters into consideration.

- Image Quality Index (IQI)
- Mutual Information (MI)
- Fusion Index (FI)
- Fusion Symmetry (FS)
- Fusion Factor (FF)
- Standard Deviation (SD)
- Entropy (EN)
- Root Mean Square Error(RMSE)
- Peak Signal to Noise Ratio (PSNR)

Image Quality Index (IQI)

IQI measures the similarity between two images (I1 & I2) and its value ranges from -1 to 1. IQI is equal to 1 if both images are identical. IQI measure is given by.

$$IQI= \frac{m_{ab}\ 2\ xy\ 2\ m_a\ m_b}{m_a\ m_b\ x^2 + y^2\ m_a^2 + m_b^2}$$

Where x and y denote the mean values of images I1 and I2 and ma^2, mb^2 and m_{ab} denotes the variance of I1 , I2 and covariance of I1 and I2.

Mutual Information (MI)

Considering two source images A and B and the fused image F, the amount of information that F contains about A and B is calculated as.

$$I_{FA}(f;a) = \sum_{f,a} p_{FA}(f,a) \log 2 \frac{p_{FA}(f,a)}{p_F(f) \cdot p_A(a)}$$

$$I_{FB}(f;b) = \sum_{f,a} p_{FB}(f,b) \log 2 \frac{p_{FB}(f,b)}{p_F(f) \cdot p_B(b)}$$

Then, the image fusion performance measure can be defined as.

$$MI_F^{AB} = I_{FA}(f;a) + I_{FB}(f;b)$$

A ***larger*** Mutual Information measure implies better quality.

Fusion Index (FI)

The fusion index (FI) is defined as

$FI = I_{AF} / I_{BF}$

Where I_{AF} is the mutual information index between multispectral image and fused image and I_{BF} is the mutual information index between the original image and fused image. The quality of fusion technique depends on the degree of fusion index.

Fusion Symmetry (FS)

Fusion Symmetry is a measure of symmetry of the fused image and is given by

$$FS = abs\left(\frac{I_{AF}}{I_{AF}+I_{BF}} - 0.5\right)$$

Where I_{AF} and I_{BF} are mutual information between source images and fused image. The quality of fusion technique depends on the degree of Fusion symmetry. Since FS is the symmetry factor, when the sensors are of good quality, FS should be as low as possible so that the fused image derives features from both input images. If any of the sensors is of low quality then it is better to maximize FS than minimizing it. Low value of fusion symmetry indicates the goodness of the fusion algorithm.

Fusion Factor (FF)

Given two images A and B, and their fused image F, the Fusion factor (FF) is.

$$FF = I_{AF} + I_{BF}$$

where IAF and IBF are the MIM values between input images and fused image. A ***higher*** value of FF indicates that fused image contains moderately good amount of information present in both the images.

Standard Deviation (SD)

Standard Deviation measures the contrast in the fused image. Fused image with ***high*** contrast would have high standard deviation.

$$SD = \sqrt{\frac{1}{MN} \sum_{0}^{N-1} \sum_{0}^{M-1} [I_f(x,y) - U_{If}]^2}$$

Where U_{If} is the mean value.

Entropy (EN)

One of the quantitative measures used in digital image processing is entropy, introduced by Claude Shannon, the entropy concept was first utilized in order to quantify the information content of messages. Larger alterations and changes in an image give larger entropy values and sharp, focused images have more changes than blurred and misrouted images.

$$\mathbf{EN = - \sum_{l=0}^{L-1} p(\ell) \log 2\, p(\ell)}$$

where p(ℓ) is the probability of gray level ℓ.

The fused image which contain the ***maximum*** of Entropy will give the best fusion technique.

Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) between the fused image and original image provides error as a percentage of mean intensity of the original error. The RMSE value is calculated as.

$$RMSE = \sqrt{\frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} (R(i,j) - (F(i,j))}^2$$

Where R(i, j) is the reference image and F(i, j) is fused image, and m and n are image dimensions. Smaller the value of the RMSE, better the performance of the fusion algorithm.

Peak Signal to Noise Ratio (PSNR)

The PSNR is used to calculate the similarity between two images. The PSNR between the reference image R and the fused image F is calculated as.

$$\mathbf{PSNR = 10 \times \log}\left(\frac{fmax^2}{MSE^2}\right)$$

Where fmax is the maximum gray scale value of the pixels in the fused image. Higher the value of the PSNR, better the performance of the fusion algorithm.

4.2 Analysis

The following tabular column show the comparison between different Transform methods with the Select-Maximum fusion rule and the proposed method. The Image Quality Index (IQI), Standard Deviation (STD), Mutual Information (MI), Fusion Index (FI), Fusion Symmetry (FS), Fusion Factor (FF), Standard Deviation (SD), Entropy (EN), Root Mean Square Error(RMSE) and Peak Signal to Noise Ratio (PSNR) are calculated and compared with the fusion methods Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Steerable Pyramid Transform (SPT), Curvelet Transform, Contourlet Transform and the Innovative Contourlet Transform,which is the proposed method.

Table 1: Performance Evaluation of Fusion Results for Medical Images.

Fusion Methods	IQI	MI	FI	FS	FF	SD	EN	RMSE	PSNR
DWT	0.4197	2.5776	3.1859	0.3432	3.684	50.2483	5.1289	40.1345	16.0604
SWT	0.4506	2.5983	3.1738	0.3519	3.6845	50.2003	5.5176	39.4941	16.2002
SPT	0.4151	2.3858	3.3533	0.1751	3.5709	47.407	5.7079	31.4616	18.2306
CURVELET	0.4283	2.3869	3.33	0.2519	4.3731	49.909	5.2058	38.525	18.4159
CONTOURLET	0.4507	2.8528	3.6588	0.0986	4.9044	58.0452	5.6156	30.3757	19.1713
PROPOSED	0.4659	3.5622	3.7904	0.0681	5.3105	60.9434	5.9826	29.1289	19.7893

The following Figure 8, Figure 9 and Figure 10 show the Graphical representation of various performance measures SD, RMSE and PSNR, MI, FI, FF and EN, IQI and FS respectively.

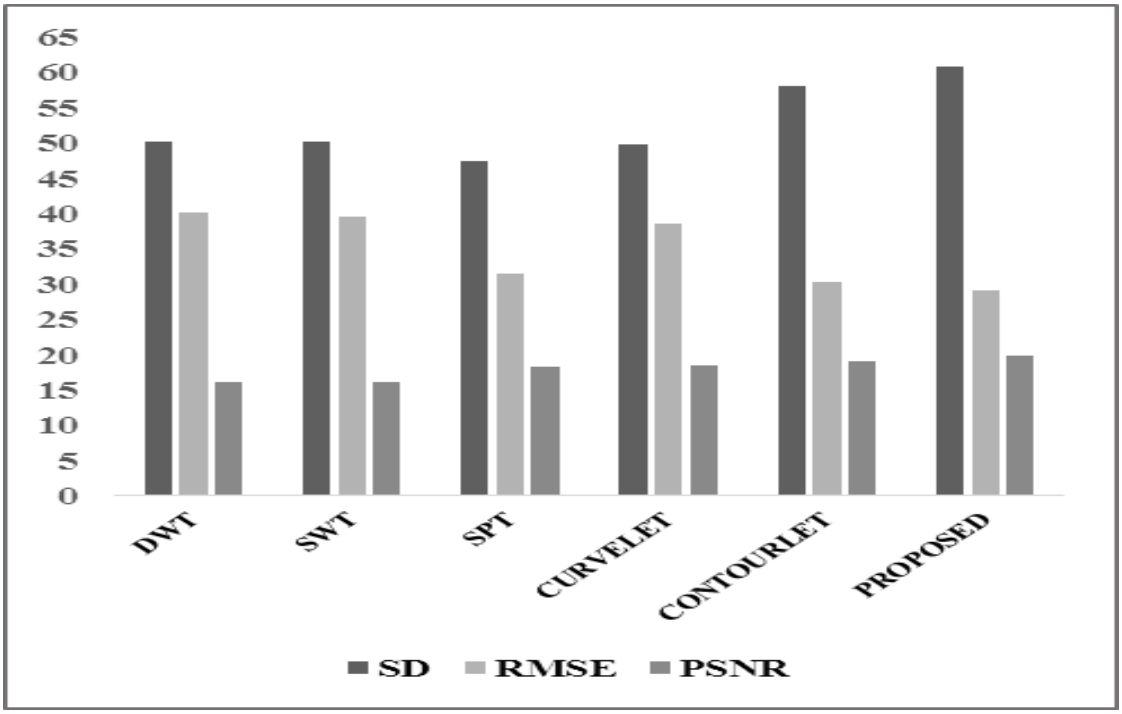


Figure 8. Performance Analysis in Respect to SD, PSNR and RMSE.

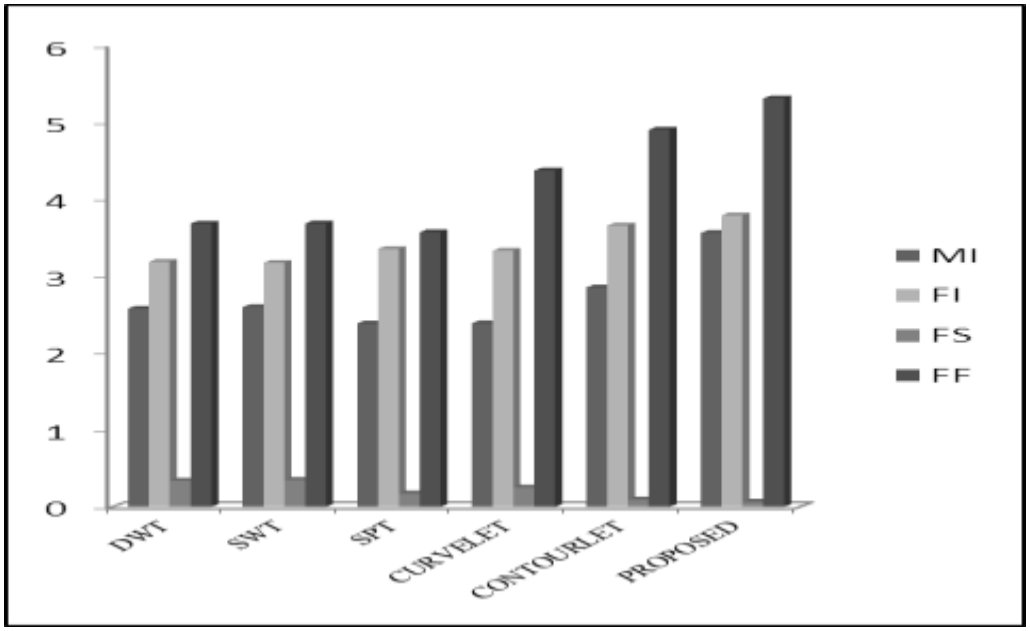


Figure 9: Performance Analysis in Respect to MI, FI, FF and EN.

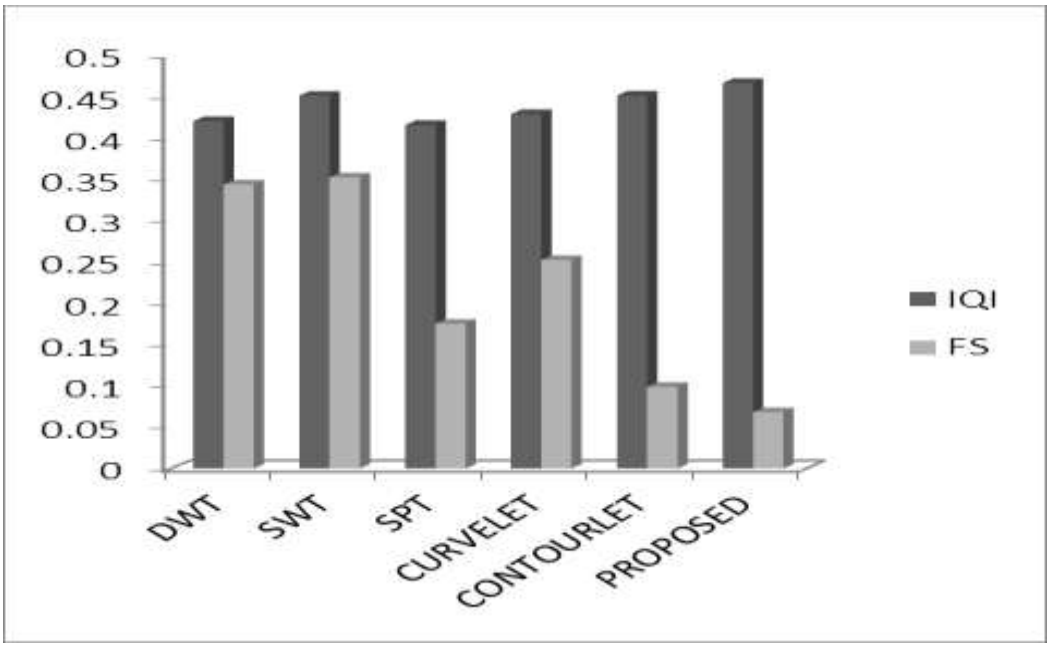


Figure 10: Performance Analysis in Respect to IQI and FS.

From the graph, it is evident that the proposed method has higher values according to SD, PSNR, MI, FI, FF, EN, IQI and has lower value according to RMSE and FS.

4.3 DISCUSSION

The field of medical nosology and observation of medical images faces many technological, scientific and social challenges.The technological advancements in imaging technologies have resulted in improved imaging accuracies. However, each modality of imaging has its own sensible limitations, that is more obligatory by the underlying nature of the organ and tissue

structures. This enforces the necessity to explore the likelihood to newer imaging technologies and to explore the likelihood of exploitation of multiple imaging modalities. The power of image fusion techniques to quantitatively and qualitatively improve the standard of imaging options makes multi-modal approaches economical and correct. The most challenge in applying image fusion algorithms is to confirm the medical relevance and aid for a far better clinical outcome.

When addressing the medical image fusion issues, the strain has been in the direction of developing algorithms that attempt to improve the imaging quality and regions of interest within images. the requirement for rising the image quality arises from the signal noise and also the physical limitations of the imaging modality. The estimation of signal noise and compensation is taken into account as a crucial drawback in medical imaging, and also theadvancements in enhancements to image quality will have a positive impact on the image fusion method.

The proposed algorithm has been implemented using Matlab 7.0. Proposed innovative contourlet transform based image fusion approach is applied to two different modality of images such as CT and MRI. In order to evaluate the fusion results obtained from different methods and compare the methods, the assessment measures are employed. The value of each quality assessment parameters of all mentioned fusion approaches are depicted in Table 1.

Our experimental results show that proposed method provides better performance and quality on compared to Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Steerable Pyramid Transform (SPT), Curvelet Transform, Contourlet Transform. Due to efficiency of the proposed method the image quality index (IQI), the similarity between reference and fused image is higher compared to IQI values from DWT, SWT, SPT, Curvelet and Contourlet transform based fusion methods. The higher values of fusion factor (FF) obtained from the proposed method indicates that fused image contains moderately good amount of information present in both the images compared to FF values obtained from DWT, SWT, SPT, Curvelet and Contourlet transform based fusion methods.The amount of information of one image in another, mutual information measure (MI) is also significantly better which shows that proposed method preserves more information compared to DWT, SWT, SPT, Curvelet and Contourlet transform based fusion methods. The other evaluation measures like root mean square error (RMSE) with lower and peak signal to noise ratio (PSNR) with higher values are also comparatively better for the proposed method.

Finally entropy, the amount of information that can be used to characterize the input image also better for images obtained from the proposed method. So it is concluded that results obtained from the implementation of the innovative contourlet transform based fusion method performs better than DWT, SWT, SPT, Curvelet and Contourlet transform based fusion methods.

5. CONCLUSION

The use of Image Fusion in the medical context is to improve confidence in diagnostics, to provide structural and functional information in the same image, to increase the reading efficiency, to quantify the difference between scans, to plan radiation therapy and more. From medical image fusion the clinicians can benefit from the complementarities of the different images to decide whether there is evidence showing the progression of the disease. In this paper, an innovative contourlet transform has been implemented and Maximum selection rule is used for fusion. Performance analysis is compared with different multi scale transforms such as Wavelet, Stationary Wavelet, Steerable Pyramid wavelet, Curvelet for the fusion of multimodality images. The obtained fusion results are compared with different evaluation parameters and proved that the proposed method provides better result.Thus the two different modality images are fused using the innovative contourlet trnsform method.The fused image obtained using innovative contourlet transform contains more useful information than the source images, thus enabling the radiologists to locate the imperfections accurately, making the treatment easier and perfect.

In this work, pixel level image fusion method is used. Spatial domain fusion method directly deal with pixels of input images. But, spatial domain based image fusion techniques often produce poor results because they usually produce spectral distortions in the fused image. In future, a new fusion method is to be developed by combining spatial and transform domain.

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