A Novel Image Fusion Technique for Medical Images Based On Digital Shearlet Transform

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ABSTRACT--- *Brain tumor is a mass of unnecessary cells becoming in the cerebrum. Primary brain tumors and metastatic cerebrum tumor are two essential sorts of cerebrum tumors. For reasons not fully realized, tumor cells develop abnormally. To precise detected size and area of brain tumor expect a key part in the diagnosis of tumors. At first, by utilizing data from both the Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) images, image registration transforms different types of data coordinations into one coordinate system. Then wavelet and contourlet transforms estimated tumor. Anyhow wavelets miss the smoothness and contourlets miss continuum theory to detect brain tumor. A novel approach based Digital Shearlet Transform (DST) comprises to remove the noise in the image by cascading multiscale decomposition and directional filtering. The low subband of DST is fused to utilize the contrast based fusion rule. The fusion rule of the selecting maximum is to be denoised in the high-pass subbands of DST. In experimental result, the DST is appraised better results in Peak signal to noise ratio (PSNR) compared with other techniques Wavelet transform, Contourlet transform techniques.*

Keywords---Image fusion, Contourlet, Digital shearlet Transform.
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1. INTRODUCTION

The Brain [1] is the most difficult part of the human body. The three pound mass of tissue processes human's intelligence, controls human behavior, initiates human body movement, holds hundred billion nerve cells. A brain tumor [2] is a growth of irregular cells called as neoplasm. It is an anomalous tissue that develops by division of uncontrolled cells. Normal cells grow in a prescribed manner as fresh cells replace damaged cells. For reasons not fully realized, tumor cells develop abnormally. non-cancerous cells and cancerous cells are classified in brain tumors. Tumors can be distinguished by exact location and types. So, to identify the location and the type of the tumor, the many techniques being utilized Magnetic Resonance Imaging (MRI), Nuclear Magnetic Resonance Imaging and Computed Tomography (CT) Scans images. Image fusion [3-4] merges multiple images to produce a faultless and reliable image. To fuse the MRI and CT images, at first, image registration transforms different types of data coordinations into one coordinate system. Fourier Transform (FT) was analyzed non-stationary signal unsuccessfully. Then wavelet analysis [5-6] enhanced the efficiency as compared with FT. whatever it may be, wavelet analysis misses the smoothness at the contours. The Contourlet transform [7-8] gets the smoothness at the contours. However the proper continuum theory is missing to detect the tumor. The DST [9-10] is used to give perfect sparse approximations to detect the exact location and type of the brain tumor.

Section-II describes the disadvanges of the Contourlet transform. Section-III describes the novel DST. In section-IV, explains the proposed method. Section-V shows the experimental results, and then Section-VI concludes the paper.

2. CONTOURLET TRANSFORM

The Contourlet Transform is augmenting the sparsity of images in excess of the Wavelet Transform. The Laplacian pyramid (LP) and directional filter banks (DFB) can be utilized to decompose the contourlet transform. Fig.1 shows the Contourlet Transform comprises of low sub band and high sub bands. The output of the low sub band is passed through the LP to get additional coefficients till the exact details of the image achieved.
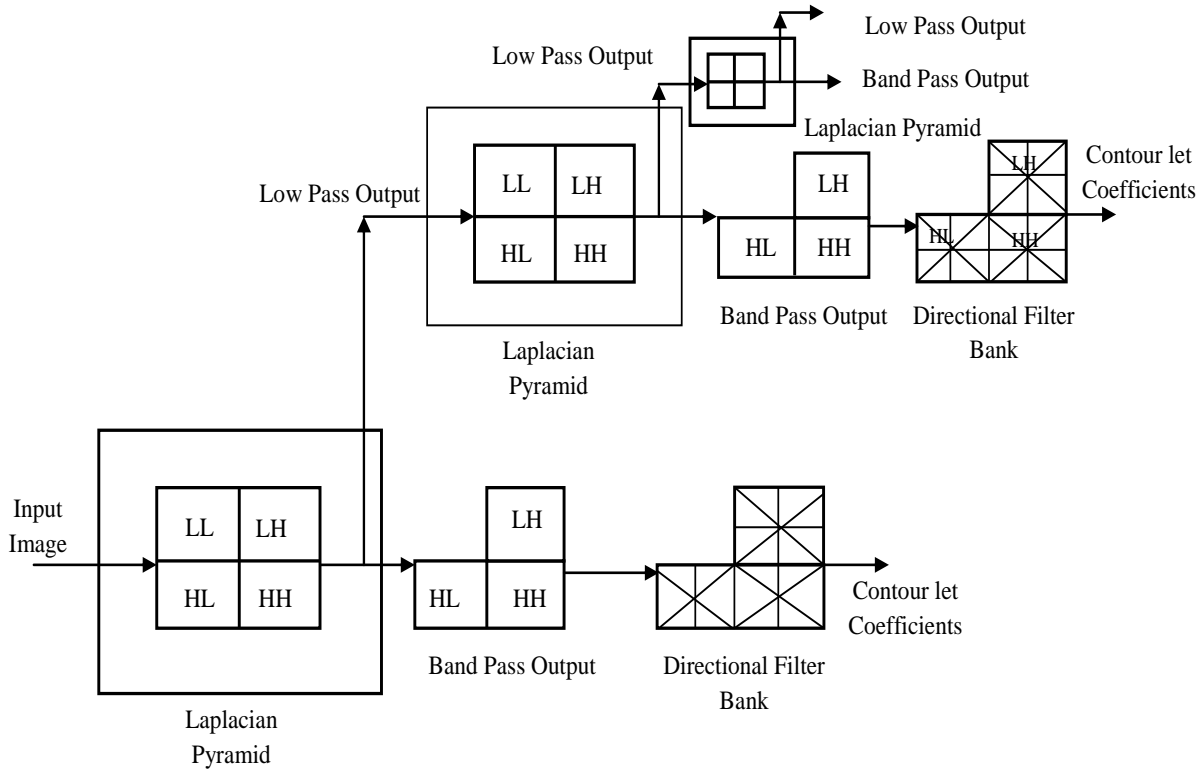
Fig.1: Design of Contourlrt Transform

To identify the location and type of the brain tumor, contourlet transform typically utilized for denoising the images. Whatever it may be, the Contourlet transform not only have more computational complexity, but also proper continuum theory is missing.

3. 3D DIGITAL SHEARLET TRANSFORM (3DDST)

Essentially, Shearlet transforms compositesthe wavelengths $L^2(\mathbb{R}^2)$.Every element $\hat{\psi}_{j,l,k}^{(d)}$supports a pair of trapezoids. And each element constraints$2^j \times 2^{2j}$ size, shown in Fig.2. The DST is used to depict the collection of shearlets presented as per below steps.

For $\mathcal{D}_0 = \left\{ (\xi_1, \xi_2) \in \hat{\mathbb{R}}^2, |\xi_1| \geq \frac{1}{8}, \left| \frac{\xi_2}{\xi_1} \right| \leq 1, j \neq 0 \right\}$and $l = -2^j, \dots, 2^j - 1$, let$\hat{\psi}^{(0)}$is distinct as

$$\hat{\psi}^{(0)}(\xi) = \hat{\psi}^{(0)}(\xi_1, \xi_2) = \hat{\psi}_1(\xi_1)\hat{\psi}_2\left(\frac{\xi_2}{\xi_1}\right) \qquad (1)$$

$$W_{j,l}^{(0)}(\xi) = \begin{cases} \hat{\psi}_2\left(2^j \frac{\xi_2}{\xi_1} - l\right)\chi_{\mathcal{D}_0}(\xi) + \hat{\psi}_2\left(2^j \frac{\xi_1}{\xi_2} - l + 1\right)\chi_{\mathcal{D}_1}(\xi) & if \ l = -2^j \\ \hat{\psi}_2\left(2^j \frac{\xi_2}{\xi_1} - l\right)\chi_{\mathcal{D}_0}(\xi) + \hat{\psi}_2\left(2^j \frac{\xi_1}{\xi_2} - l - 1\right)\chi_{\mathcal{D}_1}(\xi) & if \ l = 2^j - 1 \\ \hat{\psi}_2\left(2^j \frac{\xi_2}{\xi_1} - l\right) & otherwise \end{cases} \qquad (2)$$

As well as $\mathcal{D}_1 = \left\{ (\xi_1, \xi_2) \in \hat{\mathbb{R}}^2, |\xi_2| \geq \frac{1}{8}, \left| \frac{\xi_2}{\xi_1} \right| \leq 1, \right\}$, subsequently $\hat{\psi}^{(1)}$is distinct as

$$\hat{\psi}^{(1)}(\xi) = \hat{\psi}^{(1)}(\xi_1, \xi_2) = \hat{\psi}_1(\xi_2)\hat{\psi}_2\left(\frac{\xi_1}{\xi_2}\right) \qquad (3)$$
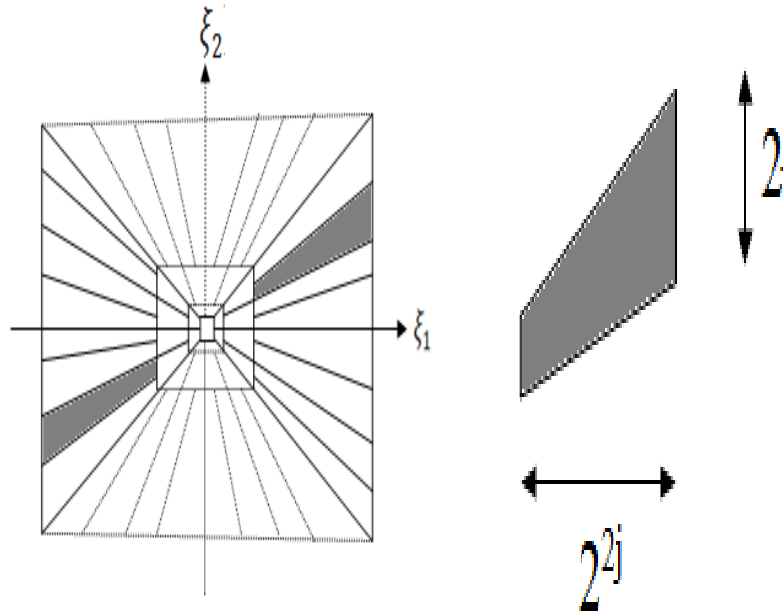
Fig.2: Tiling frequency of shearlet transform and frequency support of shearlet transform

$$W_{j,l}^{(1)}(\xi) = \begin{cases} \hat{\psi}_2\left(2^j\frac{\xi_2}{\xi_1} - l\right)\chi\mathcal{D}_0(\xi) + \hat{\psi}_2\left(2^j\frac{\xi_1}{\xi_2} - l + 1\right)\chi\mathcal{D}_1(\xi) & if\ l = -2^j \\ \hat{\psi}_2\left(2^j\frac{\xi_2}{\xi_1} - l\right)\chi\mathcal{D}_0(\xi) + \hat{\psi}_2\left(2^j\frac{\xi_1}{\xi_2} - l - 1\right)\chi\mathcal{D}_1(\xi) & if\ l = 2^j - 1 \quad (4) \\ \hat{\psi}_2\left(2^j\frac{\xi_1}{\xi_2} - l\right) & otherwise \end{cases}$$

Where $\psi_2 \subset [-1,1]$ for $1 - 2^j \leq l \leq 2^j - 1$.

From figure 2(a),the window function $W_{j,l}^{(d)}(\xi)$ is on a pair of trapezoids.The horizontal cone $\mathcal{D}_0$ and vertical cones $\mathcal{D}_1, W_{j,l}^{(d)}(\xi)$ is the superposition of two such functions when $l = -2^j$ or $l = 2^j - 1$.By utilizing this notation, for $j \geq 0, -2^j \leq l \leq 2^j - 1, k \in \mathbb{Z}^2, d = 0,1$, the Fourier transform of the shearlets can be depict as

$$\hat{\psi}_{j,l,k}^{(d)}(\xi) = 2^{\frac{3j}{2}}V(2^{-2j}\xi)W_{j,l}^{(d)}(\xi)e^{-2\pi i\xi A_d^{-j}B_d^{-l}k} \quad (5)$$

$$V(\xi_1,\xi_2) = \hat{\psi}_1(\xi_1)\chi\mathcal{D}_0(\xi_1,\xi_2) + \hat{\psi}_2(\xi_2)\chi\mathcal{D}_1(\xi_1,\xi_2)$$

The dilation matrice A^j is related with scale transformations and the dilation matrice B^j is the area-preserving geometrical transformations as rotations and shear.

$$A_0 = \begin{pmatrix} 4 & 0 \\ 0 & 2 \end{pmatrix}, B_0 = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}, A_1 = \begin{pmatrix} 2 & 0 \\ 0 & 4 \end{pmatrix}, B_1 = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \quad (6)$$

The DST of $f \in L^2(\mathbb{R}^2)$ can be computed as

$$SH_\psi = \langle f, \psi_{j,l,k}^{(d)} \rangle = 2^{\frac{3j}{2}}\int_{\mathbb{R}^2}\hat{f}(\xi)\overline{V(2^{-2j}\xi)W_{j,l}^{(d)}(\xi)}e^{2\pi i\xi A_d^{-j}B_d^{-l}k}\ d\xi \quad (7)$$

$$\sum_{d=0}^{1}\sum_{l=-2j}^{2j-1}\left|W_{j,l}^{(d)}(\xi_1,\xi_2)\right|^2 = 1 \quad (8)$$

$$|\hat{\varphi}(\xi_1,\xi_2)|^2 + \sum_{d=0}^{1}\sum_{j\geq0}\sum_{l=-2j}^{2j-1}\left|V(2^{2j}\xi_1,2^{2j}\xi_2)\right|\left|W_{j,l}^{(d)}(\xi_1,\xi_2)\right|^2 = 1 \; for \; (\xi_1,\xi_2)\in\hat{\mathbb{R}}^2 \qquad (9)$$

4. PROPOSED METHOD

In this section, the proposed method steps describe that how the tumor being detected, shown in Fig.3.

1. Read the MR and CT images from the image sources and image registration is set into same coordinate system.

2. DST domain local direction band limited contrast at m^{th} scale and n^{th} direction. $SH_{LF}^{I_1}(i,j)$, $SH_{LF}^{I_2}(i,j)$ and $SH_{m,n}^{I_1}(i,j)$, $SH_{m,n}^{I_2}(i,j)$ are the low band and high band coefficients of the image sources I_1 and I_2 respectively.

$$I_1(i,j) = SH_{LF}^{I_1}(i,j) + \sum_{m,n} SH_{m,n}^{I_1}(i,j)$$

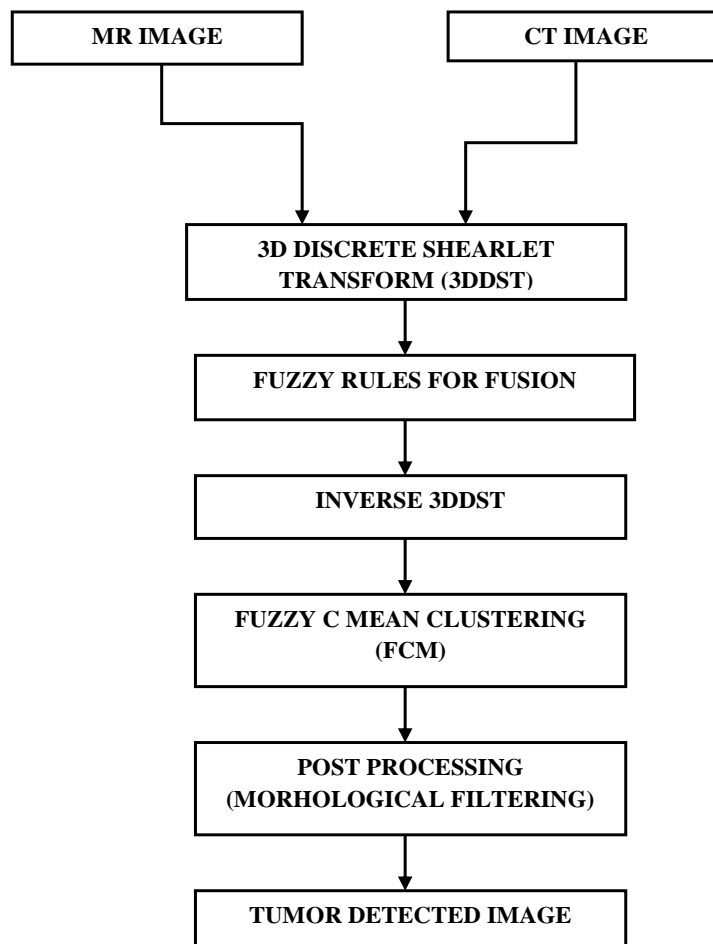$$I_2(i,j) = SH_{LF}^{I_2}(i,j) + \sum_{m,n} SH_{m,n}^{I_2}(i,j)$$

Fig.3. Proposed Architecture of the Image Fusion Tecniques

3. For low subband coefficients, the contrast pixel can be defined as

$$I_{c_1}(i,j) = \left| SH_{LF}^{I_1}(i,j) - \bar{I}_1(i,j) \right|$$

$$I_{c_2}(i,j) = \left| SH_{LF}^{I_2}(i,j) - \bar{I}_2(i,j) \right|$$

$$I_L(i,j) = \begin{cases} SH_{LF}^{I_2}(i,j) & if\ I_{c_2}(i,j) \geq I_{c_1}(i,j) \\ SH_{LF}^{I_1}(i,j) & otherwise \end{cases}$$

Where $\bar{I}_1(i,j)$, $\bar{I}_2(i,j)$ are the average intensities of all pixels of the images I_1 and I_2 respectively.

For high subband coefficients,

$$I_H(i,j) = \begin{cases} \sum_{m,n} SH_{m,n}^{I_1}(i,j) & \sum_{m,n} SH_{m,n}^{I_1}(i,j) \geq \sum_{m,n} SH_{m,n}^{I_2}(i,j) \\ \sum_{m,n} SH_{m,n}^{I_2}(i,j) & otherwise \end{cases}$$

4. Fuse the both low subband coefficients and high subband coefficients.

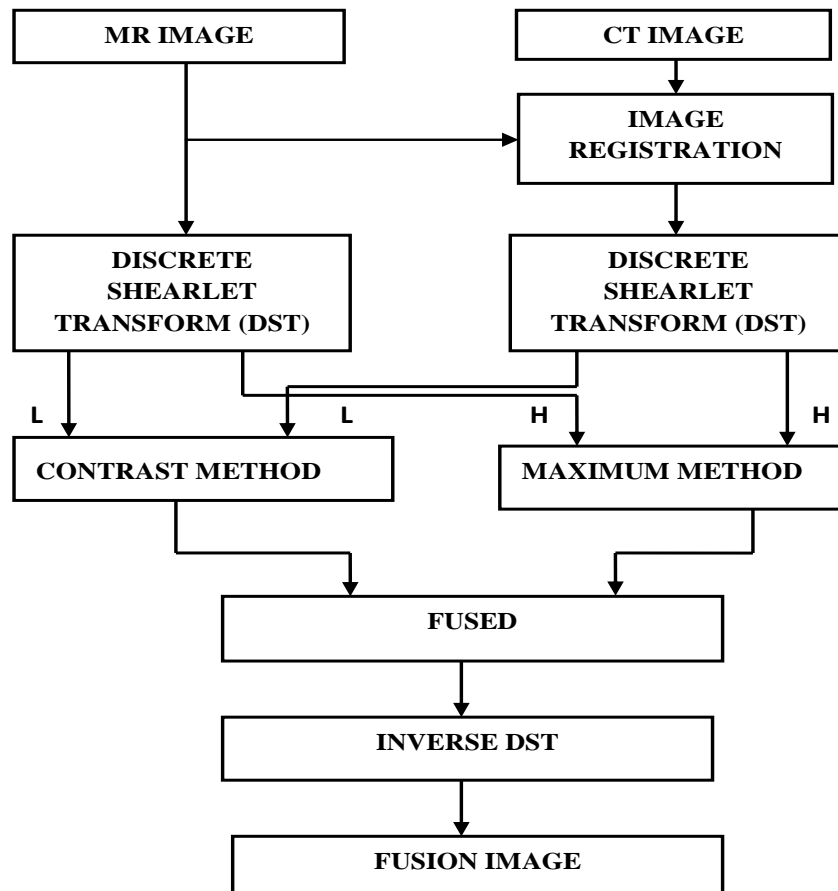5. Apply the Inverse Discrete Shearlet Transform to then obtain the fused image sequence.

Fig.3. Proposed Architecture forbrain tumor detection in image fusion technique

5. RESULT AND DISCUSSION

Based on the proposed technique steps, the brain tumor is detected, shown in Fig. 4. As compare with the wavelet transform and Contourlet transforms in image fusion technique, the proposed method gives better PSNR results. Based on Table -1, the proposed technique has performed well as compare wavelet transform and Contourlet transform.

Peak Signal to Noise Ratio (PSNR): Better PSNR value gives better result,

$$PSNR = 20 \log_{10} \left[\frac{L^2}{\frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(I_r(i,j) - I_f(i,j) \right)^2} \right],$$

Where L = No. of gray levels in the image, $I_r(i,j)$ and $I_f(i,j)$ are the reference and fused images respectively.

Table-1: Comparisons of PSNR values with Different methods of Transforms

TYPE OF TRANSFORM	PEAK SIGNAL TO NOISE RATIO (PSNR)
Wavelet	10.67
Contourlet	36.76
Proposed	39.42

(a)   (b)   (c)
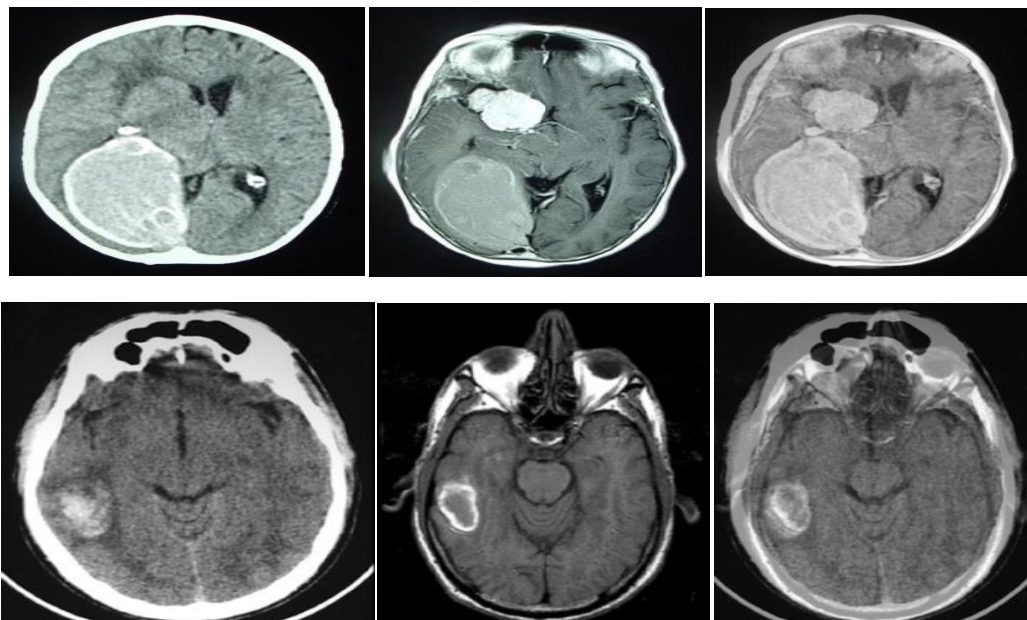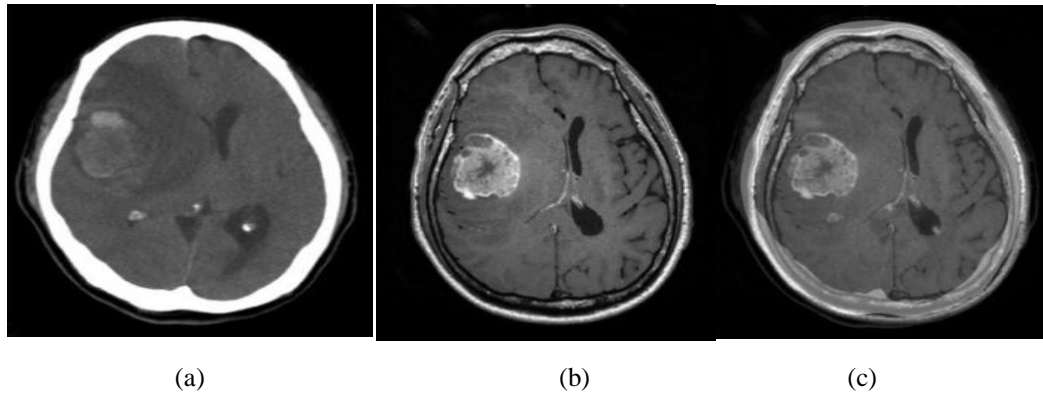
Fig.4: (a) CT Images (b) MR Images (c) DST based Fused Image

6.   CONCLUSION

The paper proposes a novel fusion technique for medical images based on digital shearlet transform. The fusion technique has processed by using wavelet transform and Contourlet transforms, however, these transforms results do not stern with the artifacts, specifically in medical applications.

If noise is contained in both MR and CT images, the noise images may get the fusion image all together with the important pixels. However, the DST is preprocessing the both MRI and CT images on the images for the reason of denoise. The Experiment results exhibit that the proposed fusion technique has more PSNR as compare with the wavelet transform and Contourlet transforms and extremely enhances the fused image quality.

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