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A Novel 3d Digital Shearlet Transform Based Image Fusion Technique Using Mr and CT Images for Brain Tumor Detection

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Abstract: A tumor is abnormal tissue that develops by uncontrolled cell division. Regular cells develop in a controlled manner as new cells supplant old or harmed ones. For reasons not completely comprehended, tumor cells reproduce uncontrollably. To exact identification of size and area of brain tumor assumes an indispensable part in the diagnosis of tumors. Initially, wavelet and contourlet transforms based calculation for tumor identification which uses compliment and redundant data from the Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) images. But wavelets won't get the smoothness along the contours and computational complexity of Contourlet Transform is too high and proper continuum theory is missing to detect brain tumor. A novel approach based 3D Digital Shearlet Transform (3DDST) comprises in a cascading of a multiscale decomposition and a directional filtering stage to remove noise in the image. In 3DDST, the low-pass subband is fused to use the fusion rule of the weighted sum. The fusion rule of the selecting maximum is to be denoised in the high-pass subbands. In experimental result, the 3DDST is evaluated better results in Peak signal to noise ratio (PSNR), Entropy, Space frequency and standard deviation compared with other fusion techniques Wavelet, Contourlet transform methods in terms of both visual quality and objective evaluation.

Key words: Wavelet · Contourlet · 3DDST · FCM

INTRODUCTION

The Brain [1] is the most unpredictable organ in the human body. It processes human's each thought, activity, memory, feeling and knowledge of the world. This mass of tissue weighing in at around 1.4 kilograms, holds an amazing one hundred billion nerve cells, or neurons forming a gigantic neural network. A brain tumor [2] is a growth of anomalous cells inside the brain called as neoplasm. It is irregular tissue that grows by uncontrolled cell division. Regular cells grow in a controlled manner as new cells replace old or damaged ones. For reasons not completely comprehended, tumor cells reproduce uncontrollably. Tumors are also classified as non-cancerous (benign) or cancerous (malignant). However, all can cause serious problems. Tumors are characterized by where exactly located, what kind of tissue it composed of, whether it is benign or malignant. And the reason of most brain tumors is not known. To detect the tumor, the different techniques are being widely utilized to get the images for processing like Magnetic Resonance Imaging, Nuclear Magnetic Resonance Imaging and Computed Tomography (CT) Scans. Image segmentation is basically a process of pixel classification, wherein the image pixels are divided into subsets by assigning the individual pixels to classes. For Image segmentation, Fuzzy C Mean (FCM) clustering algorithm suits to detect the brain tumor. Image fusion [3-5] merges data from imaging sensors to generate a fused image with faultless and more reliable data than other source images. Image Fusion is a lot of consideration in wide mixed variety of applications, such as, computer vision, concealed weapon detection, remote sensing, military surveillance, medicinal diagnosis. As compared with source images, the fused images are more suitable for perception and comprehension. Frequently, the multiple sensor data are excess and complementary. The fusion of such data reduces the uncertainty and increases the exactness.

Fourier Transform (FT) was unsuccessful to analyze a non-stationary signal. The MRI and CT images were processed by utilizing the wavelet transform. The basic of wavelet analysis [6-8] was based image fusion to improve

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the efficiency of brain tumor detection. Wavelets tolerate the complex information, such as speech and image processing to be decomposed into basic structures at different positions and scales and then reconstructed with high precision. Wavelets in 2-D are good at eliminating noise for efficient analysis and isolating the discontinuities at the edges, however, won't get the smoothness along the contours and won't hold directionality and anisotropy. These are the main properties to introduce the contourlet transform. The Contourlet [9-13] transform is another transform for image decomposition method. But the Contourlet Transform has more computational complexity and proper continuum theory is missing in this approach. Shearlets [14-15] were alleged composite wavelets, as a multivariate extension of wavelet framework. One of the unique characteristics of shearlets is the utilization of shearing to control directional selectivity, as opposed to rotation utilized by curvelets. The weakness is that minimally backed shearlets are not tight edges and likewise the synthesis process requirements to be performed by iterative methods. The 3DDST is focused around the directional multiscale shearlet framework representation and it reproduces the frequency decomposition of the 3DDST, to give ideally sparse approximations for the classification of 3D information.

Section-II explains the detecting brain tumor using contourlet transform and its disadvantages. In section-III, Describes the 3DDST. In section-IV, proposes the proposed architecture. And the experimental results shown in Section-V then finally in Section-VI concludes this paper.market share of wind turbine, for conventional variable speed generators it is an alternative model. The DFIG has wound rotor induction generator, with its rotor windings via collection of two ac/dc converters back to back, it is connected to grid, where its stator winding is directly connected to grid [1, 2]. These converters are sorted for only one third of the turbine rated power, this topology achieves an decoupled control of reactive and active power and proven to be cost effective[3, 4]. During grid fault the DFIGs produce a major drawback. Due to grid fault there is a voltage drop at stator windings, it results in an abrupt change of the DFIG stator flux and due to magnetic coupling it leads an over current to the rotor winding. Then to the large fluctuations of dc-link voltages and to the semiconductors of rotor side converters, this overcurrent may cause an severe damages [5, 6].

Contourlet Transform: Compression, Denoising, Feature Extraction and Enhancements are the parsimonious representation of the signal in many signal processing tasks. The Contourlet Transform [9] (CT), aimed at enhancing the representation sparsity of images over the Wavelet Transform (WT). Mainly Contourlet transform possess the directionality and anisotropy properties, for having basis functions at many directions at various aspect ratios.

The Laplacian pyramid (LP) and directional filter banks (DFB) are used to develop the contourlet transform. Figure 1. shows the contourlet transformation consists of frequency components like low pass output (LL-LowLow), band pass output (LH-LowHigh, HL-HighLow and HH-HighHigh). The low pass output is

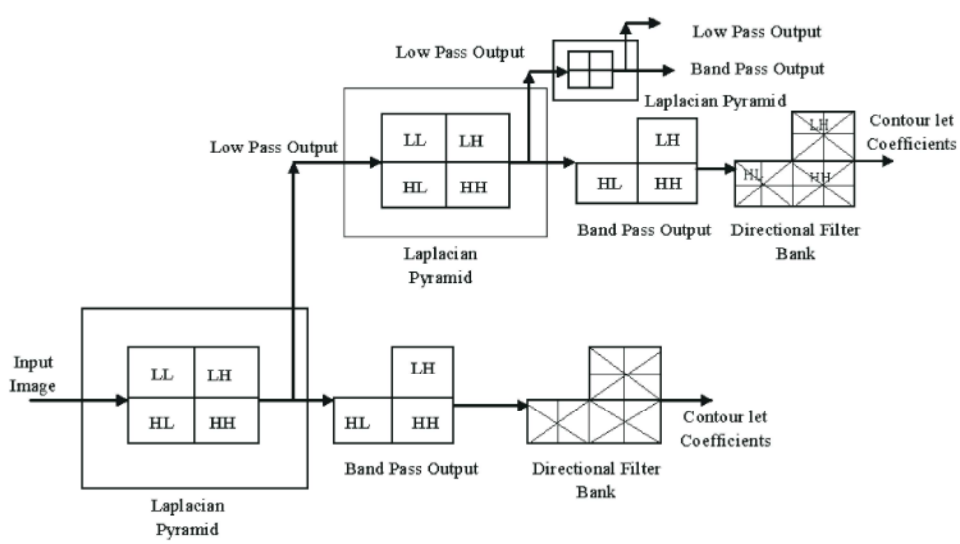

Fig. 1: Design of Contourlet Transform

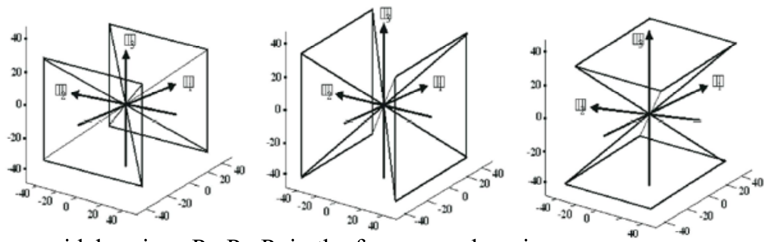

Fig. 2: Illustrates the pyramidal regions P_1, P_2, P_3 in the frequency domain

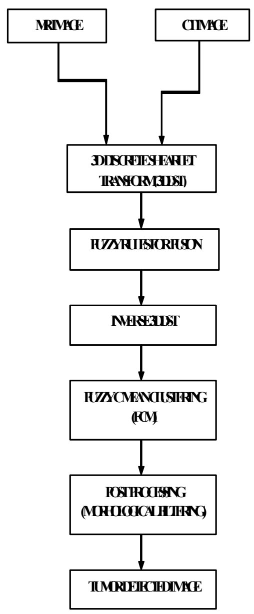

Fig. 3: Proposed Architecture of the Image Fusion Techniques to detect the Brain Tumor

passed through the Laplacian Pyramid to acquire more coefficients until the fine details of the image obtained. To detect the brain tumor, contourlet transform mostly utilized for the reduction and denoising of images. But the computational complexity of Contourlet Transform is too high and proper continuum theory is also missing in this approach.

3D Digital Shearlet Transform (3DDST): The 3D digital shearlet transform can be depicted as the cascade of multi-scale decomposition, based on the Laplacian pyramid filter, emulated by a phase of directional filtering. The major innovation of 3DDST is to be denoised the images by utilizing the direction filtering. The directional filtering design endeavors to reproduce the frequency decomposition provided by utilizing a process based on the pseudo-spherical Fourier transform. Hence, reduces the computation complexity of the 3DDST and improves the visual quality. The shearlet methodology function declares at different scales and locations and according to different orthogonal transformations controlled by shearing matrices. For 3D (dimension D = 3), a shearlet system is acquired by suitably combining three systems of functions associated with the pyramidal regions in which the Fourier space R ^^3is partitioned, shown in Figure 2.

$$P_1 = \left\{(\xi_1, \xi_2, \xi_3) \in \mathbb{R}^3 : \left|\frac{\xi_1}{\xi_2}\right| \geq 1, \left|\frac{\xi_1}{\xi_3}\right| \geq 1\right\},$$

$$P_2 = \left\{(\xi_1, \xi_2, \xi_3) \in \mathbb{R}^3 : \left|\frac{\xi_2}{\xi_1}\right| \geq 1, \left|\frac{\xi_2}{\xi_3}\right| \geq 1\right\},$$

$$P_3 = \left\{(\xi_1, \xi_2, \xi_3) \in \mathbb{R}^3 : \left|\frac{\xi_3}{\xi_1}\right| \geq 1, \left|\frac{\xi_3}{\xi_2}\right| \geq 1\right\},$$

The 3D shearlet systems related to the pyramidal regions P_d are described for d= 1, 2, 3, $l = l_1, l_2 \in \mathbb{Z}^3$,

$$\left\{\psi_{j,k,l}^{(d)} : j \geq 0, -2^j \leq l_1, l_2 \leq 2^j, k \in \mathbb{Z}^3\right\} \qquad (1) \tag{1}$$

where the 3D shearlet generator filter ψ is defined as

$$\psi_{j,k,l}^{(d)} = \left|\det A_{(d)}\right|^{-\frac{j}{2}} w(2^{-2j}\xi) F_{(d)}\left(\xi A_{(d)}^{-j} B_{(d)}^{[-l]}\right) e^{2\pi i \xi A_{(d)}^{-j} B_{(d)}^{[-l]} k} = \hat{g}_{J-j}(\xi_1) \hat{\varphi}_{j,k_1,l}^{d}(\xi_1,\xi_2) \hat{\varphi}_{j,k_2,l}^{d}(\xi_1,\xi_3) \hat{\varphi}_{j,k_3,l}^{d}(\xi_2,\xi_3) \tag{2}$$

$DST_{j,k,l}^{3D}(f_J)(\tilde{m}) = (f_J * \psi_{j,k,l}^{-d})(\tilde{m})$ for j = 0,…, J-1, $\tilde{m} = (2^{J-j} c_1^i m_1, 2^{J-j/2} c_2^i m_2, 2^{J-j/2} c_3^i m_3)$ with the sampling constant c_1^i, c_2^i, c_3^i selected then $\tilde{m} \in \mathbb{Z}^3$.

$$F_{(1)}(\xi_1,\xi_2,\xi_3) = V\left(\frac{\xi_2}{\xi_1}\right) V\left(\frac{\xi_3}{\xi_1}\right), \quad F_{(2)}(\xi_1,\xi_2,\xi_3) = V\left(\frac{\xi_1}{\xi_2}\right) V\left(\frac{\xi_3}{\xi_2}\right),$$

$$F_{(3)}(\xi_1,\xi_2,\xi_3) = V\left(\frac{\xi_1}{\xi_3}\right) V\left(\frac{\xi_2}{\xi_3}\right).$$

The anisotropic dilation matrices $A_{(d)}$ are defined as

$$A_{(1)} = \begin{pmatrix} 4 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{pmatrix}, A_{(2)} = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 2 \end{pmatrix}, A_{(3)} = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 4 \end{pmatrix}.$$

And the shear matrices are defined as

$$B^{[l]}_{(1)} = \begin{pmatrix} 1 & l_1 & l_2 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}, B^{[l]}_{(2)} = \begin{pmatrix} 1 & 0 & 0 \\ l_1 & 1 & l_2 \\ 0 & 0 & 1 \end{pmatrix}, B^{[l]}_{(3)} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ l_1 & l_2 & 1 \end{pmatrix}$$

Proposed Method: In this paper, the proposed method needs to be detected the brain tumor by the description of the proposed architecture, shown in Figure.3.

- Read the MR and CT images from the image sources and find its size in rows and columns wise.
- These input images are transformed to 3D Discrete Shearlet Transform (3DDST) domain and it is decomposed into low-pass subband coefficients $DST_0^{3D_A}(f_j)(\tilde{m}), DST_0^{3D_B}(f_j)(\tilde{m})$ and high-pass subband coefficients $DST_{j,k,l}^{3D_A}(f_j)(\tilde{m}), DST_{j,k,l}^{3D_B}(f_j)(\tilde{m})$ of MR and CT image sources.
- If the energy of subband coefficient is extensive and its entropy information is large, the coefficient helps more importance to the fused image. High-pass subband coefficients is used for eliminating noise by filter banks.
- Apply the Inverse 3D Discrete Shearlet Transform to the fused coefficients and then obtain the fused image sequence.
- Then segment the image by utilizing an FCM clustering algorithm. FCM segments the image based on the membership function of the center pixel and its neighboring pixels.
- Finally, after segmentation, the morphological filtering operations are performed to separate the tumor region from the image. Structuring element is a morphological technique to explore an image with small shapes. To compare with the corresponding pixels, structuring element is placed at all possible regions of an image.

RESULT AND DISCUSSION

The proposed method detects the brain tumor, shown in Figure 4. To detect the brain tumor, Proposed method describes its advantages with experimental results to compare with the wavelet and contourlet transforms in image fusion technique. It is clear from the proposed method that it is performed well than wavelet and

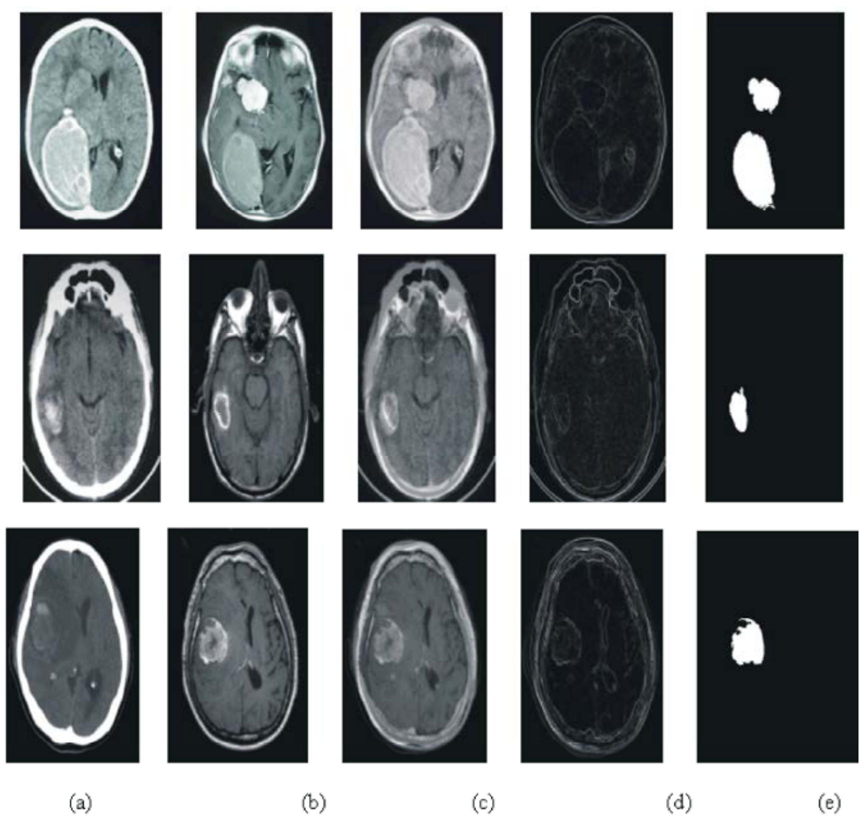

Fig. 4 : (a) CT Images (b) MR Images (c) Fusion Image using 3DDST (d) Segmented Image (e) Tumor Detected and located Image.

Table 1: Metrics For Performance Evaluation of Different Satellite Images

S.No.	Metrics for performance	Equation	Properties
1.	Peak Signal to Noise Ratio (PSNR)	$PSNR = 20\log_{10}\left[\frac{L^2}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_r(i,j) - I_f(i,j)\right)^2}\right]$ Where L = No. of gray levels in the image	When the fused and reference images are similar. Higher value implies a better fusion, Its value will be high
2.	Segmentation Accuracy (SA)	$\frac{\text{Total number of correctly classified pixels}}{\text{Total number of pixels}}$	The Image segmentation prompts to more compact image representation.
3.	Entropy	$H^{LF} = -\sum_{i=1}^{m}\sum_{k=1}^{n} DST_{j,k,i}^{3D}(f_j)(\tilde{m})\log_2 DST_{j,k,i}^{3D}(f_j)(\tilde{m})$	An image with high information content would have high entropy. Entropy is used to measure the information content of an image, is sensitive to noise and other unwanted rapid fluctuations.
4.	Spatial Frequency	Row frequency of image $RF = \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=2}^{N}[I_f(x,y) - I_f(x,y-1)]^2}$ Column frequency of image $CF = \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=2}^{N}[I_f(x,y) - I_f(x-1,y)]^2}$ Spatial Frequency Criterion SF is: SF = $\sqrt{RF^2 + CF^2}$	This spatial domain frequency indicates the overall activity level in fused image.
5.	Standard Deviation	$\sigma = \sqrt{\sum_{i=0}^{L}(i-\bar{i})^2 h_{I_f}(i)}, \quad \bar{i} = \sum_{i=0}^{L} i h_{I_f}$ $h_{I_f}(i)$ -The normalized histogram of fused image $I_f(x, y)$. L - no. of frequency bins in the histogram.	Standard deviation is composed of signal and noise parts. And it would be more efficient in the absence of noise. An image with high contrast would have a high standard deviation.

Table 2: Comparisons of Different methods of Transforms

S.No.	Type of Transform	PSNR	SA	Entropy	Spatial Frequency	Standard Deviation
1.	Wavelet	10.67	43	5.122	18.04	62.96
2.	Contourlet	36.76	71	8.110	19.05	72.12
3.	Proposed	40.27	92	8.547	19.98	78.81

contourlet transforms. We can observe that the entropy, spatial frequency, segmentation accuracy, standard deviation of the fused image based on the 3DDST method has shown better results than the other methods.

CONCLUSION

The paper proposes a novel 3DDST for image sequence fusion and denoising. When the fusion process is performed, the wavelet and contourlet transforms image fusion methods do not compact with the artifacts. If MR and CT images contain noise, the noises may be transferred into the fusion image together with useful pixels. Hence, The 3DDST is performed as a preprocessing on the images for the purpose of denoise in MR and CT images. FCM performs segmentation process to the fused image. Morphological filtering performs to separate the tumor region from the image. The proposed method described its advantages compare with the wavelet and contourlet transforms. Experiments exhibit that the proposed method enhances extraordinarily the quality of the fused image sequence.

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