

A Comparative study between Contourlet and Wavelet Transform for Medical Image Registration and Fusion

Akshata M, Aparna BV, Sathyasri Donthi, Nupur Jain and Saritha Chakrasali

Abstract: Contourlet Transform is an emerging technique which captures directionality and smooth contours that are predominantly present in medical images. Image Registration is a fundamental task used in image processing to match reference and sensed images taken at different times, from different sensors or from different viewpoints to bring images into geometric alignment. The term Fusion means in general an approach to extraction of information acquired in several domains. Both registration and fusion provide effective information to the specialists for diagnosis in the field of medicine. This paper aims at registration and fusion of mono modal and multimodal medical images using Contourlet Transform. A comparative analysis has also been made between the Wavelet and Contourlet transform for medical image registration and fusion.

Keywords: Computed Tomography, Contourlet Transform, Entropy, Fusion, Magnetic Resonance Imaging, Mutual Information, Registration, Wavelet Transform

1 INTRODUCTION

In the field of medicine, imaging plays a very important role. Various modalities available are CT (Computed Tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography). Due to the advent of new diseases, complementary information from different modalities [1] is required by specialists for diagnosis, medication and treatment.

Image fusion can be defined as a process of combining two or more images into a single image without any loss of information. The objective of image fusion is to combine complementary as well as redundant information from multiple images to create a fused image output, which becomes reliable and much easier to be comprehended by people. Therefore, the new image generated should contain a more accurate description of the scene than any of the individual source image and is more suitable for human visual and machine perception or further image processing and analysis task [2]. This information can be used for different purposes like human visual and machine perceptions, diagnosis, analysis. Image registration is a vital problem in medical imaging before a fusion, in clinical diagnosis using medical images; integration of useful data obtained from separate images is often desired [1]. Important applications of image fusion include medical imaging, microscopic imaging, remote sensing, computer vision, and robotics [3].

Image Registration is the determination of one to one mapping between the co-ordinate in space and those in another such that points are mapped to each other. Therefore, it is the process of transforming different sets of data into one co-ordinate system [4]. The sensed images

need to be aligned geometrically with respect to reference image for better observation. Specifically registration aims at the integration of disparate and complementary data in order to enhance the information apparent in the images, as well as to increase the reliability of the interpretation.

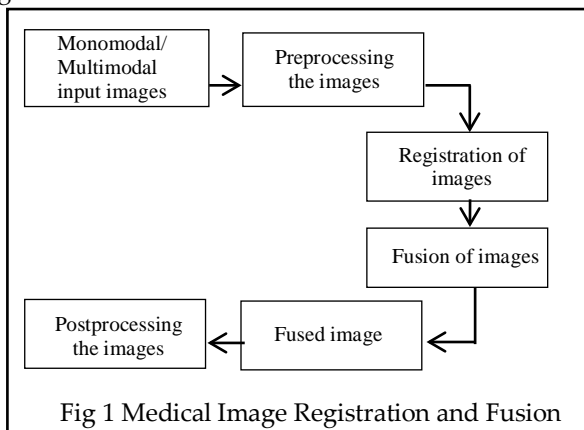
For medical diagnosis, Computed Tomography(CT) provides the best information on denser tissue with less distortion. Magnetic Resonance Image (MRI) provides better information on soft tissue with more distortion. In this case, only one kind of image may not be sufficient to provide accurate clinical requirements for the physicians. Therefore, the fusion of the multimodal medical images is necessary [1].

Medical image representation follows various conditions such as Multi resolution where the representation should allow images to be successively approximate from coarse to fine resolution, Localization where the basis elements should be localized in both spatial and frequency domains, Critical sampling where representation should form a basis or a frame with small redundancy for some application, Directionality where basis elements oriented at a variety of directions and anisotropy which is used to capture smooth contours in images, basis elements using a variety of elongated shapes with different aspect ratio [5]. The medical images are characterized by curved shapes and contours. Further limited work has been done in the area of medical image processing using Contourlet Transform [5],[6][7].

The various medical image fusion algorithm proposed by researchers [8],[9] work in wavelet domain. Wavelets are finite duration oscillatory functions with zero average value. The irregularity and good localization properties

make them better basis for analysis of signals with discontinuities. Wavelets are well adapted to point singularities (discontinuities), but have a problem with orientation selectivity. Directionality and Anisotropy conditions are not provided by wavelet. One of the emerging transforms in the various fields of image processing is Contourlet Transform which provides all of the above conditions. Hence an effort has been made in this paper to apply Contourlet Transform for registration and fusion of monomodal and multimodal images. Contourlets capture directionality and smooth contours which are pre dominantly present in medical images resulting in an image expansion which is a directional multiresolution analysis frame work.

The Fig 1 shows the overall view of registration and fusion process that is applied to the medical images in these paper.Both mono modal images or multi modal images can be processed. The input images are preprocessed by filtering in order to remove noise which is predominant in medical images. These filtered images are further registered using the mutual information method [10]. This orients and scales the images. Thus the registered images are fused. The output fused image is post-processed to remove noise which is introduced during the fusion process. Finally in this paper, the fused image is quantitatively evaluated using the performance metrics like MSE (Mean Square Error) and PSNR (Peak Signal to Noise Ratio) and then for comparative evaluation, both Contourlet and wavelet transform are applied for registration and fusion.



2 MEDICAL IMAGE REGISTRATION

Filtering is the preprocessing step in image registration. There are many types of filters such as gaussian, median and mean filters. The median filter is a nonlinear digital filtering technique used to remove noise. It is widely used in digital image processing because, under certain conditions, it preserves edges while removing noise. It is a robust and an average filter [11]. Gaussian filter does not provide the desired results for medical images because

MSE is very high for the output images. It reduces details and consumes more time [12]. Hence in this work, median filter has been used.

Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors. The registration process is conducted using Mutual Information as a similarity measure [10].

Mutual Information is a direct measure of the amount of information common between the two images i.e. similarity measure. Mutual Information maximization methods are useful in medical image registration domains where well defined features exist and can be easily extracted. It can be defined using the below formula as [13]:

$$\text{MutualInformation} = \text{entropy}(X) + \text{entropy}(Y) / \text{Joint Entropy}(X, Y) \quad (1)$$

The entropy H(X) of a discrete random variable X is defined by

$$H(X) = -\sum_x p(X) \log p(X) \quad (2)$$

The joint entropy H(X, Y) of a pair of discrete random variables (X, Y) with a joint distribution p(x, y) is defined as[14]

$$H(X, Y) = -\sum_{x,y} p(X, Y) \log p(X, Y) \quad (3)$$

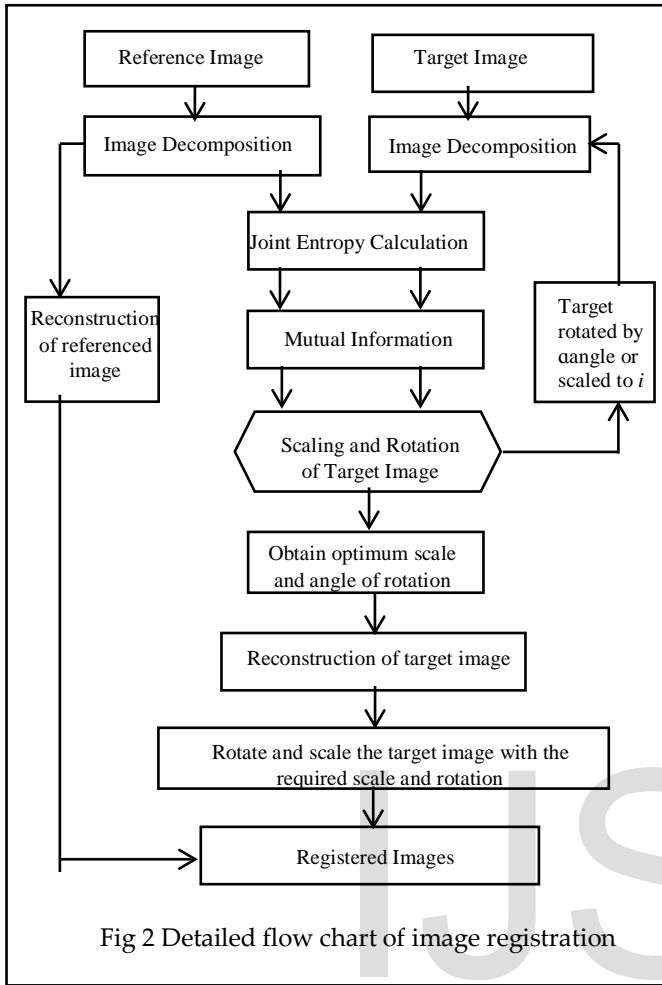
which can also be expressed as

$$H(X, Y) = -E \log p(X, Y) \quad (4)$$

The detailed flowchart in Fig 2 shows the steps followed in this work for registration for both mono modal and multimodal images.

3 MEDICAL IMAGE FUSION

Image fusion is the process by which two or more images are combined into a single image retaining the important features from each of the original images. The fusion of images is often required for images acquired from different instrument modalities or capture techniques of the same scene or objects (like multi-sensor, multi-focus and multimodal images). The fusion framework in the Contourlet Transform domain developed in this work is shown below in Fig 3.



Medical Image Fusion process involves various steps. First, the input images are divided into coarse scales and fine scales. Coarse scales represent the high frequency components and fine scales represent low frequency components in the input images. Low frequency components contain overall details of the image while the high frequency components contain details about edges and textures. Then, these coefficients of the input images are decomposed. Second, the coarse scales and the fine scales in the source images are separately fused based on statistical fusion rule using Contourlet Transform. Separate fusion rules are applied on these fine scales and coarse scales to obtain the fusion coefficients.

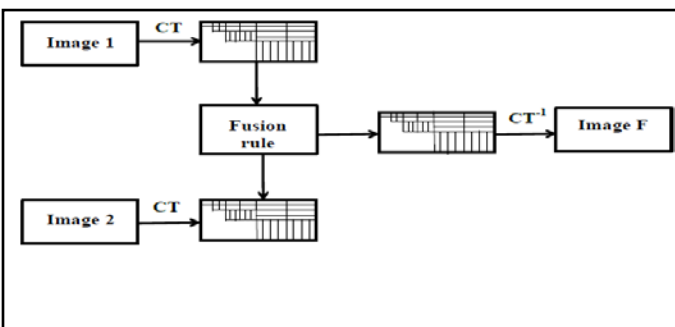
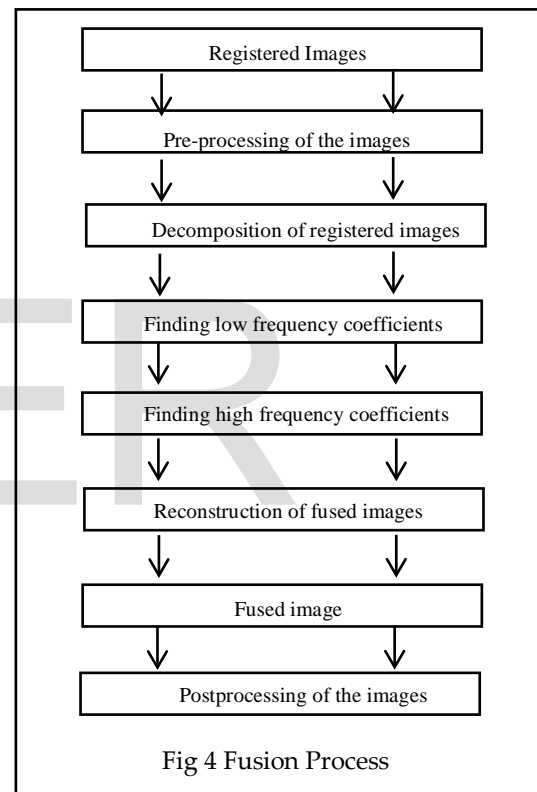


Fig 3 Fusion framework based on Contourlet Transform

The fused image is obtained by inverse Contourlet Transform from these fusion coefficients. The two different statistical fusion rules are discussed. These rules are analysed experimentally thereby examining the performance of the image fusion in both Wavelet and Contourlet Transform domain.

The detailed flowchart in Fig 4 shows the steps followed in this work for fusion of both mono modal and multi modal images.



The fusion scheme implemented in this work is explained as follows:

After the process of registration, the registered images are decomposed in multi-scale and multi-direction by Contourlet Transform. The transform coefficients of referenced image and target image are Y_{Ref} and Y_{Tar} , respectively. The transform coefficients of the fused image can be denoted by Y_F . Then, process the coefficients based on the following rules:

- For the coefficients of the low frequency, fusion with the average rule:

$$Y_F = (Y_{Ref} \{1\} + Y_{Tar} \{1\}) / 2 \quad (5)$$

- For the coefficients of the high frequency, if l_i , the decomposition level parameters of directional filter

bank in the vector $nlevels$, is not equal to 0, fuse by the rule of selecting the coefficients of greater region energy using region consistency check in Eq. (6).

$$E_x(i, j) = \sum_{i \leq m, j \leq n} (Y_X(i, j))^2, X = Ref, Tar, \dots (6)$$

by Eq. (6). With Eq. (7), the high frequency subbands of the fused image can be constructed. Also, at the same time, the fusion decision map is obtained by Eq. (8).

$$Y_F(i, j) = \begin{cases} Y_{Ref}(i, j), E_{Ref}(i, j) \geq E_{Tar}(i, j) \\ Y_{Tar}(i, j), E_{Ref}(i, j) < E_{Tar}(i, j) \end{cases} (7)$$

$$Map(i, j) = \begin{cases} 1, E_{Ref}(i, j) \geq E_{Tar}(i, j) \\ 0, E_{Ref}(i, j) < E_{Tar}(i, j) \end{cases} (8)$$

Finally, the region consistency check is done based on the fusion-decision map. If a pixel is to come from the source image A but with the majority of its surrounding neighbors from B, this pixel will be switched to come from B [15].

Entropy is calculated on the low frequency components of the input images within a 3-by-3 window and whichever having higher values of entropy were selected as the fusion coefficients among the low frequency components. For the high frequency components, regional energy is calculated over a 3-by-3 window using the formula

$$E_k(i, j) = \sum_{m=-2}^2 \sum_{n=-2}^2 \sum_{s=-2}^2 \sum_{d=-2}^2 W(m+3, n+3) \cdot (C_k^{s,d}(i+m, j+n))^2 (9)$$

where $C_k^{s,d}$ is the Contourlet Transform coefficient corresponding to scale s and direction d at position (i,j) for the image k . Further the coefficient is chosen as the fused coefficient according to the following formula

$$C_F^{s,d}(i, j) = \begin{cases} C_{Ref}^{s,d}(i, j), E_{Ref}(i, j) \geq E_{Tar}(i, j) \\ C_{Tar}^{s,d}(i, j), otherwise \end{cases} (10)$$

The fused image is reconstructed from the fused coefficients in Contourlet Transform.

4 RESULTS

Input datasets

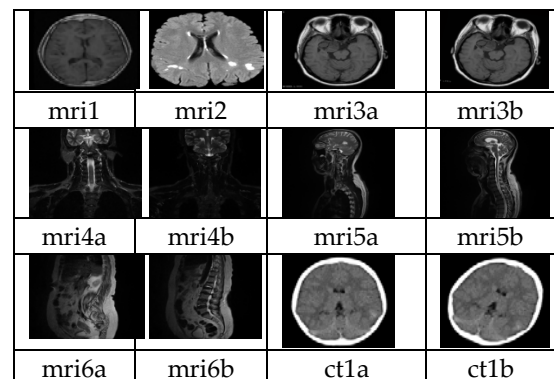
The statistics of the input images is as given in the Table 1. Fig 5 shows the Input MRI and CT images.

Registration

The dataset for the registration and fusion process consisted of ten MRI and seven CT medical images. The input images were decomposed into different levels to perform registration. Initially, registration was conducted for mono modal medical images and then extended for multimodal images. The target/sensed images obtained could be either rotated by an unknown degree of angles and/or not scaled with respect to the reference image. Thus the sensed images are rotated by an appropriate angle and/or scaled accordingly.

Table 1 Datasets Tabulation

Sl No	Input Image	Dimension	Size ondisk (in K Bytes)
1	mri1	512*512	236
2	mri2	512*512	56
3	mri3a	512*512	60
4	mri3b	512*512	180
5	mri4a	512*512	216
6	mri4b	512*512	168
7	mri5a	512*512	140
8	mri5b	512*512	148
9	mri6a	512*512	236
10	mri6b	512*512	224
11	ct1a	512*512	200
12	ct1b	512*512	168
13	ct2a	512*512	228
14	ct3	512*512	52
15	ct4a	512*512	60
16	ct4b	512*512	52



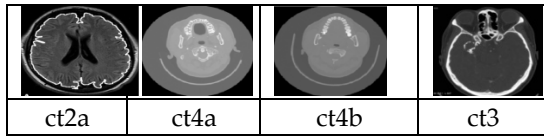


Fig 5 Input Data

MI is calculated to determine the level of decomposition to be selected. The Table 2 gives the values of MI for mono modal images and Table 3 gives the values of MI for multi modal images which are used as performance metric to compare between the Contourlet and Wavelet Transforms and the better one can be inferred.

Based on the MI values obtained from the tables 2 and 3, it is inferred that level 2 gives the best results out of all the levels for both Contourlet and Wavelet Transform. The Fig 7a to 7d show the registered mono modal images and Fig 8a to 8c show the registered multi modal images using Contourlet Transform and the Wavelet Transform for the level 2 decomposition.

Table 2 MI values for monomodal Datasets

a) mri3a-mri3b b) mri5a-mri5b c) ct1a-ct1b d) ct4a-ct4b

Data Sets	MI	
	Contourlet	Wavelet
a	9.1964	2.6398
b	6.3960	6.3065
c	10.9461	2.0569
d	3.7515	3.2357

Table 3 MI values for multimodal Datasets

a) ct1a-mri1 b) mri2-ct2a c) mri3a-ct3

Data Sets	MI	
	Contourlet	Wavelet
a	10.7993	2.2664
b	7.1278	2.6036
c	13.5748	2.5079

Fusion

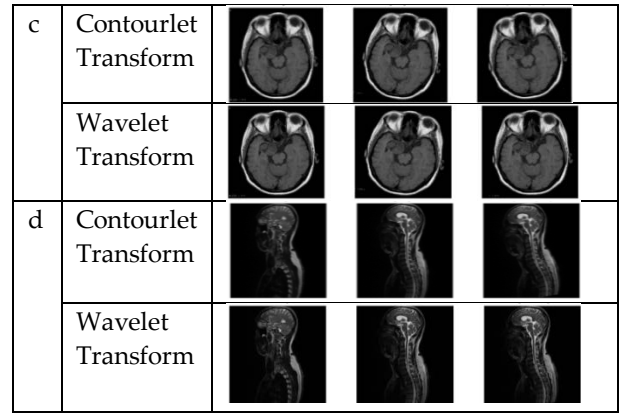
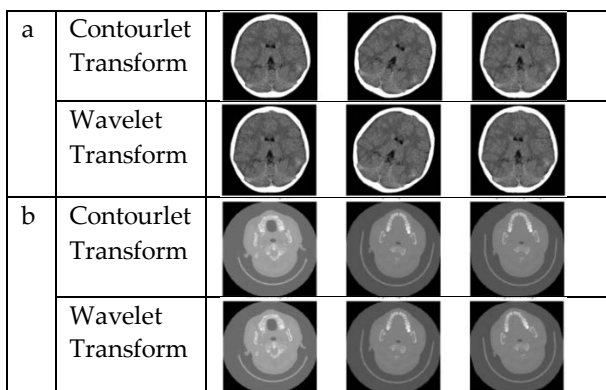


Fig 7 Registered mono modal images

a) Data set 1- ct1a, ct1b b) Data set 3- ct4a, ct4b
 c) Data set 4- mri3a, mri3b d) Data set 6- mri5a, mri5b

The registration and fusion process for both mono modal and multi modal images was conducted. Fusion is performed on registered images considering the low and high frequency coefficients which produce a resultant output fused image. The fusion process for mono modal and multi modal medical images is performed at different levels in two different domains which are Contourlet Transform and Wavelet Transform.

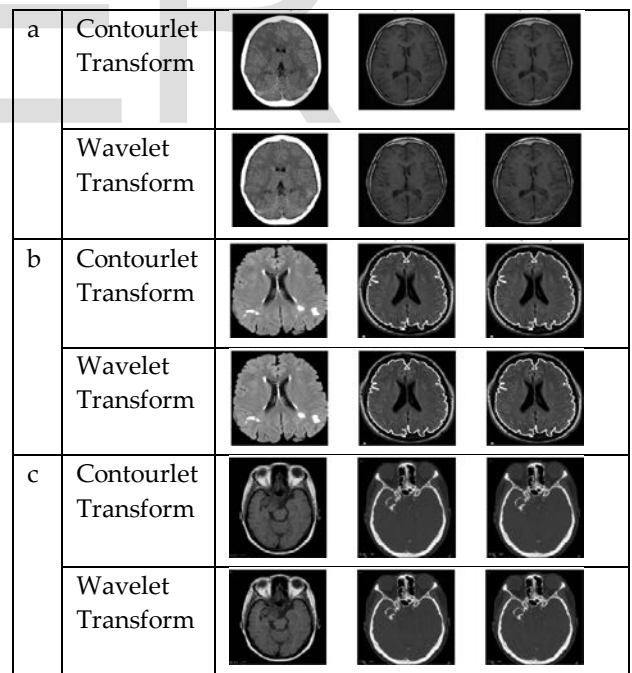


Fig 8 Registered multi modal images a) Data set 1- ct1a mri1
 b) Data set 3- mri2-ct2a c) Data set 4- mri3a ct3

Table 4 and Table 5 gives the MSE and PSNR values of the mono modal images and the multi modal images respectively in both the domains i.e. Contourlet and

Wavelet. Based on the MSE and PSNR values obtained from Table 4 and Table 5, it was inferred that level 2 decomposition gives the best results out of all the levels.

The Fig 9a) to 9d) show the fused mono modal images and Fig 10a) to 10c) show the fused multi modal images using Contourlet Transform and the Wavelet Transform for level 2 decomposition.

Table 4 MSE and PSNR values for monomodal datasets
a) mri3a-mri3b b) mri5a-mri5b c) ct1a-ct1b d) ct4a-ct4b

Data Sets	Contourlet		Wavelet	
	MSE	PSNR	MSE	PSNR
a	0.0107	67.8706	25.3755	34.0867
b	0.0064	70.0121	23.3125	34.4549
c	0.0034	72.7660	17.5153	35.6966
d	0.0036	72.4918	130.1832	26.9853

Table 5 MSE and PSNR values for multimodal datasets
a) ct1a-mri1 b) mri2-ct2a c) mri3a-ct3

Data Sets	Contourlet		Wavelet	
	MSE	PSNR	MSE	PSNR
a	0.022672	64.5759	161.5183	26.0486
b	0.038159	62.3488	192.1816	25.2937
c	0.025950	64.0233	142.2007	26.6018

5 CONCLUSIONS

- This paper aims at highlighting the significance of using Contourlet Transform for medical image registration and fusion.
- The various conclusions that were derived at the end of this paper are very helpful for establishing the model for mono modal and multimodal registration and fusion using Contourlet Transform. The statutory compliance requirements i.e. MSE, PSNR are identified and calculated. Acceptance criteria such as the image quality, MRI and/or CT scans of same patients are used in this paper.
- The use of median filter in the preprocessing and post processing stages improves the image quality as median filters preserve edges while removing noise. The noise introduced in the fusion process is also removed so that a superior fused image is obtained by using median filters. The post

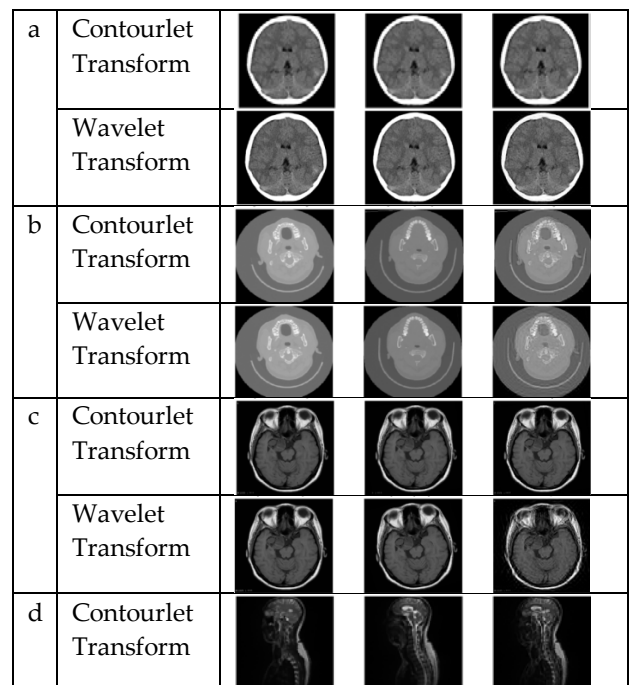
processing also includes sharpening of the output image to enhance the image quality.

- Contourlet Transform level 2 decomposition gives better MI value, hence improving the registration of two images. The quality of the fused image obtained at the level 2 decomposition of Contourlet Transform is very much improved than the fused image obtained at the other levels.
- The model is successful for both mono modal and multimodal images. Further the order of input images does not make much significant differences. The Registration results show that the images fused in the Contourlet Transform domain exhibit improved image quality than the fused images obtained from wavelet domain.

Hence this paper has highlighted the noteworthy improvements in registration and fusion of mono modal and multimodal medical images using the Contourlet Transform.

FUTURE ENHANCEMENT

- Optimization of the above code can be done using various optimization algorithms like Genetic Algorithm (GA), Particle Swam Optimization (PSO), Support Vector Machine (SVM) can be performed.
- The registration and fusion process can be even applied on modalities such as Functional-MRI (F-MRI) and Positron Emission Tomography (PET).



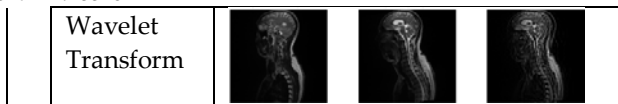


Fig 9 Fused mono modal images

- a) Data set 1- ct1a , registered ct1b b)Data set 3- ct4a,registered ct4b c) Data set 4- mri3a, registered mri3b
d) Data set 6- mri5a, registered mri5b

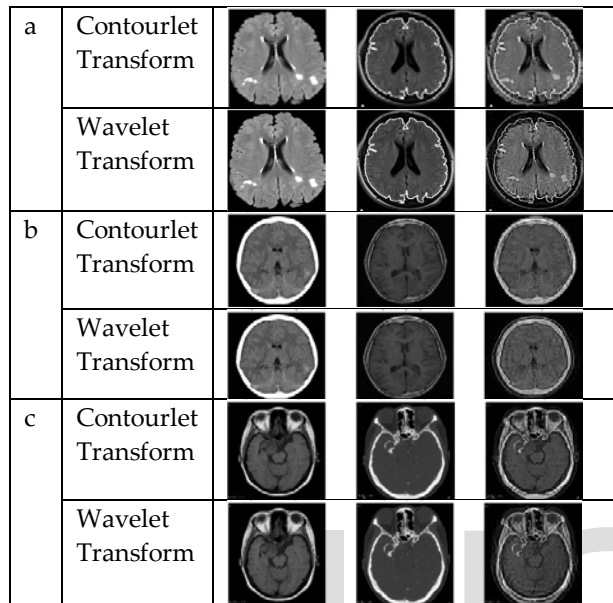


Fig 10 Fused multi modal images

- a) Data set 1- ct1a, registered mri1 b)Data set 3- mri2, registered ct2a c) Data set 4- mri3a, registered ct3

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AUTHORS DETAIL



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