# Enhanced Image Registration Technique for Medical Image Segmentation

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***Abstract* - In image processing and image analysis the final result is obtained by combining information from various resources. To obtain better result from combined information, image registration plays an important role, which is a earlier step in image segmentation. Generally it follows feature extraction, feature matching, transformation and sampling, dominant extracted features and matching algorithm gives the better registration accuracy. In proposed system contourlet transform and mutual information is combined to increase the accuracy in registration process. Contourlet transform extracts efficient curves and edges from MRI images, these features from MRI brain images helps to match the information using mutual information. Performance comparison of proposed results shows high performance using Contourlet transform.**

**Index Terms -** Feature extraction, Transform modeling, Image resampling, Contourlet transform, Mutual Information.

## I. INTRODUCTION

The processing of transforming different forms of data into single co-ordinate system is called image registration. Data may be different images, data which is reconstructed from different sensors, depths, times or viewpoints [1]. It is used in computer vision applications, medical imaging, biological imaging, and satellite imaging. Registration is important in order to match or fuse the data which is obtained from different measurements. The discrete expansion of curvelet transform is known as contourlet transform, first it is processed in continuous domain [2] using multi-scale filtering and then undergo with a block ridge let transform [3] on each band pass data, later it is directly used in frequency partitioning without using ridge let transform . Instead of key points contourlet transform captures curves; apart from curvelets and contourlet many transformation techniques are developing which efficiently represent geometrical regularity, for example band lets, the edge-adapted multiscale transform [3] etc, but these techniques need edge detection stage which is followed by adaptive representation.

Contourlet representation is a type of fixed transform, these characteristics made contourlet transform to be effectively applied in a computer vision tasks, similar to wavelets. In computer vision techniques Magnetic Resonance Imaging (MRI) play an important role, it is used in medical examination, assistant diagnosis of brain tumors and breast cancers owing to its high resolution to soft tissues and no damage to human body during acquisition. Medical knowledge and experience of doctors can obtain the information's like sizes, locations, shapes and other pathological features of brain tumors. According to the information in MRI images are used to make scientific and reasonable therapeutic treatment. Because there are several MRI examinations for every patient in the whole therapeutic treatment, each of which can give data in multiple sequences, it is a large amount of data to be dealt with for the doctors. Long time of hard work will inevitably lead to mistakes in the diagnosis of the tumor contours for the doctors. Moreover, it is subjective for the doctors to determine the state of the diseases according to their medical knowledge and clinical experiences. Therefore, developing an automatic or a semi-automatic computer-aided diagnosis system is meaningful in real medical treatments, which can release the workload of doctors and improve the accuracy by giving objective results. Resulting problem is a important point in the research field of medical image processing and a lot of algorithms and work have been proposed to try to solve this problem.

## II. PROPOSED METHODOLOGY

Brain tumor detection and classification algorithms normally uses T2 weighted MRI slice image, but in some cases we cannot assure that we can get correct vision of tumor, it is necessary to fuse the multiple information like T1 weighted MRI slice and PD MRI slice to get accurate result. Here we use registered images for good image fusion result, so image registration is important pre-processing step in our system. The block diagram of our methodology is shown in Fig. 1. The three slices of a image is considered for the input image. These images are preprocessed. The Contourlet transform is applied to the preprocessed images and edges are extracted to carry out registration process. These registered slices of images are fused then region growing method is applied for brain tumor segmentation by user interface selecting the location.

Normally image registration techniques carried out by following 4 general steps, i.e. from Feature Extraction to Image Resampling. In feature extraction method salient and dominant features are extracted from sensed and reference images automatically and both image features are compared. In proposed methodology Contourlet Transformation model is used to represent the geometrical parameters. The medical images are characterized by curved shapes and contours. Further limited work has been done in the area of medical imaging using Contourlet Transform.

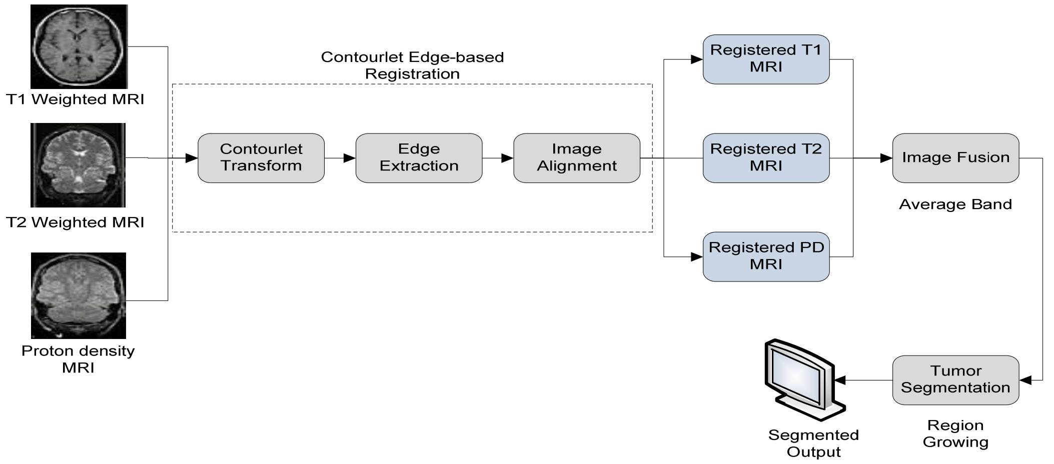



Fig. 1: Block Diagram of the Proposed Model.

Proposed Algorithm Steps:

- Input as source image and image to be registered
- Apply contourlet transform on both the image and reconstruct the images
- Calculating the joint histogram values of both reconstructed images
- Mutual information and its maximum value are determined
- Scale and the angle of rotation are computed
- Rotate the image to angle of rotation computed and scale the image to scale value obtained

### A. *Contourlet Transform*

In signal processing tasks like de-noising, compression, enhancement and feature extraction, by Contourlet Transform the image is represented efficiently. This transforms aimed to improve the sparse representation of the image over the Wavelet Transform. The ability to capture directional information is limited in the wavelet transform, which is the main drawback. The multi-scale and directional representation of image is considered in which the intrinsic geometrical structures is captured. The properties of the Contourlet Transform: directional property i.e., basis functions at number of directions, and the anisotropy property i.e., basis functions at appears at different aspect ratios. When the other geometrical representations are compared to the Contourlet Transform, it is observed that the Contourlet Transform is efficient wavelet and relatively simple.

The purpose for which is to represent as directional multi-resolution image that captures and represent the singularities efficiently with smooth object boundaries. Its lower redundancy and the filter bank construction which is efficient make the contourlet transform an attractive computational framework. The dimensional filter bank used in contourlet transform decomposes the image into many subbands at multiple-scales. It is accomplished with Laplacian pyramid and directional filter bank at each scale. The first directional decomposition and second multi-scale decomposition stages are independent because of this contourlet transform. Each scale can be decomposed into arbitrary power of 2's number of directions and different scale can be decomposed into different numbers of directions. This helps contourlet to achieve flexibility in process of decomposition.

Here f(t) is the 2D function and it decomposes to scale J with j1 directions using discrete contourlet transform [7].

$$a_J[\vec{n}] = < f, \phi_{J,n} > = \int_{\vec{t}} f(\vec{t}) e^{-j} \phi(2^{-j}\vec{t} - \vec{n}) \overrightarrow{dt} \quad (1)$$

$$c_{J,k}{}^{(l_j)}[\vec{n}] =< f, \lambda^{(l_j)}{}_{J,k,n} >= \int_{\vec{t}} f(\vec{t}) e^{-J} \lambda^{(l_j)}{}_{j,k,n}(\vec{t}) \overrightarrow{dt} \quad (2)$$

$$\lambda^{(l)}{}_{j,k,n}(\vec{t})\overrightarrow{dt} = \lambda^{(l)}{}_{j,k}\left(\vec{t} - 2^{j-1} S_k^{(l)}(\vec{n})\right) = \sum_{\vec{x}\in Z^2} d_k^{(l)}(\vec{x}) \mu_{j,x}\left(\vec{t} - 2^{j-1} S_k^{(l)}(\vec{n})\right); \vec{n} \epsilon Z^2 \quad (3)$$

$$\mu_{j,2n+k_l}(\vec{t}) = 2^{-j} \psi^{(i)}(2^{-j}\vec{t} - \vec{n}) \quad (4)$$

$$S_k^{(l)} = \begin{cases} diag(2^{l-1}, 2) & for\ 0 \le k < 2^{l-1} \\ diag(2, 2^{l-1}) & for\ 2^{l-1} \le k < 2^l \end{cases} \quad (5)$$

Where $0 \le i \le 3$, $0 \le k \le 2l - 1$, $j = 1,2,\ldots,J$, and $k$ is a downsampling rate with ratio 2 for each dimension.

$$k_0 = (0,0)^T$$
$$k_1 = (1,0)^T$$
$$k_2 = (0,1)^T$$
$$k_3 = (1,1)^T$$

Therefore, we rewrite "(3)" as

$$\lambda^{(l)}{}_{j,k,n}(\vec{t}) = \sum_{i=0}^{3} \sum_{\vec{x}\in Z^2} d_k(\vec{x}) 2^{-j} \psi^{(i)}(2^{-j}\vec{t} - 2^{-1} S_k \vec{n} - 2^{-1}\vec{x} + 2^{-1} k_i) \quad (6)$$

$a_j[\vec{n}]$ and $c_{J,k}{}^{(l)}[\vec{n}]$ are approximation coefficients and detail coefficients respectively as in "(2)". $W_{j,k}^{(l)}$ is several directional subband which is decomposed using filterbank. Contourlet function $\lambda^{(l)}{}_{j,k,n}(\vec{t})$ has compact support with width of c2j and length of $j + l - 2$ in the scale j. Also, it has L-order directional vanishing moment (DVM). For a contourlet function $\lambda^{(l)}{}_{j,k,n}(\vec{t})$ constructed from an iterated filter bank as in "(5)", it has an L-order DVM along direction $u$ if the discrete-time Fourier Transform $W_k^{(l)}(e^{j\omega_1}. e^{j\omega_2})$ the associated filter $W_k^{(l)}[\vec{n}]$ also has L-order zeros along the line $u1w1 + u2w2 = 0$.

$$\gamma_{j,k}^{l}(\vec{t}) = \sum_{\vec{m}\in z^2} w_k^{(l)}[\vec{m}] \emptyset_{j-1,m}(\vec{t}) \quad (7)$$

The frequency partition is done using contourlet transformation is as shown in Fig. 2. The scales are divided to four, eight directional subbands and from coarse-scales to the fine-scales respectively.

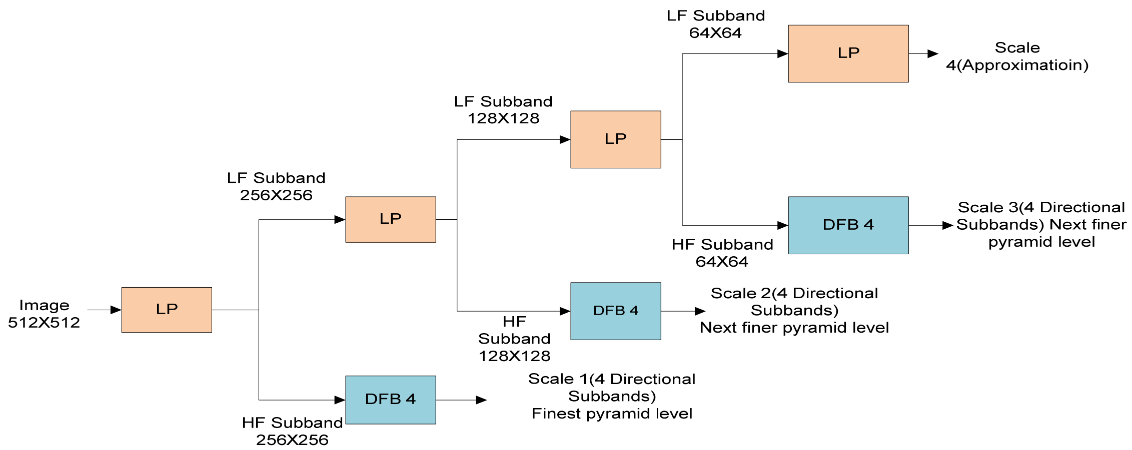



Fig. 2: Decomposition process of Contourlet Transform for a 512 X 512 image using Laplacian pyramid. [7]

Contourlet Transform uses pyramidal Directional Filter Bank (DFB) for a local, multi resolution and directional expansion of image. The DFB is combination of Laplacian Pyramid captures the discontinuity points, and directional filter banks links these discontinuities into linear structures. Fig. 2 shows the dataflow of Contourlet Transform for a 512X512 image.

*B. Mutual Information*

The measurement of amount of common information between two images is known as Mutual Information (MI). The different transformation estimates during the image registration are evaluated [7]. These transformations determine that variations in the degree of overlap between images which is better than entropy.

Mutual information can also be considered as measurement of how one image explains well the other image; it is computed using “8”. It is maximized at the optimal alignment.

$$I(A,B) = \frac{H(A) + H(B)}{H(A,B)} \tag{8}$$

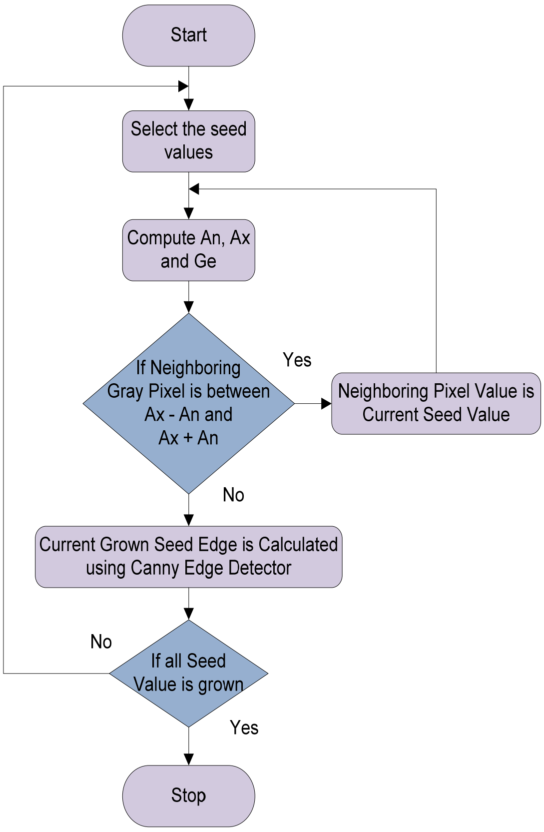



Fig. 3: Flow Diagram Region Growing Algorithm. [14]

### C. *Region Growing Algorithm*

Region growing segmentation algorithm provides better segmentation results for MRI brain images, because algorithm performs well with respect to noise. Fig. 3 shows the flow diagram of region growing; the first procedure is to select seed point or set of seed points in an image, the initial growing procedure starts from the exact location of seed point, before that expected value(Ax), entropy(An), and hyper entropy(Ge) are computed using cloud model computing[15]. By using this computed characteristics region of interest is calculated and segmented using canny edge detector .

## III. RESULTS

The proposed method takes the multimodal images as its input. The contourlet transform is applied to both the source and target images or sensed and reference images. The images are reconstructed after truncating to the most significant bits. Then the image registration is done using mutual information.

There two types of data: source image and target image. Target image is the one which is to be registered. Source image is the one which is taken as reference image for registration. Source image can be considered as the original image and Target is the rotated and scaled image, which is to be registered to the source image considered.

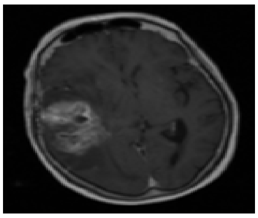


Fig. 4 (a) Source Image

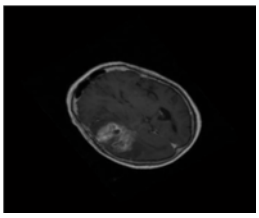
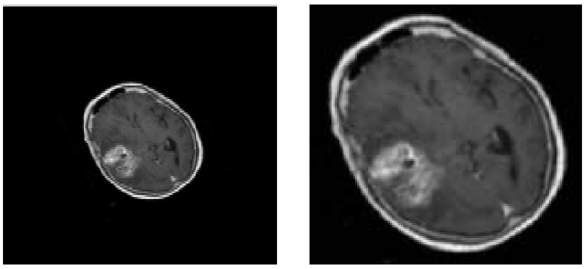


Fig. 4 (b) Target Image

The image in Fig. 4(a) is the source image and image in Fig. 4(b) is the target image that to be registered. Here image registration is done using mutual information. Therefore the source image must be mapped to target image and registration is done. Joint histogram features are calculated from both source image and target image and extracted features are normalized using "(9)", where $J_h$ is the joint histogram similarly Marginal Entropy is calculated from normalized histogram using "(10)" where $N_h$ is the normalized histogram. Mapping source image with target image during registration process is done by using mutual information as shown in "6".

$$N_h = \frac{J_h}{No\ of\ rows * No\ of\ Coloums} \quad (9)$$

$$Hy = Hy + N_h * (log2 * \quad (10)$$



(a) Image when rotated and scaled

(b) Image when matched with the Reference Image

Fig. 5: Intermediate Results

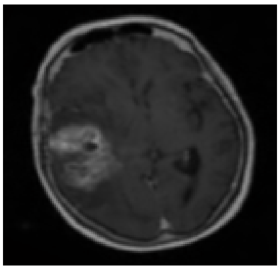


Fig. 6: Registered Image

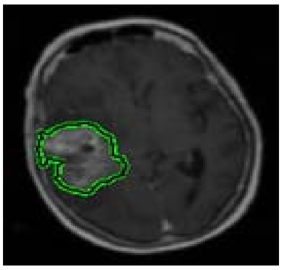


Fig. 7: Tumor Region Detected Image

The image in fig 5(a) represents original image when rotated and fig 5(b) represents the resultant image when source and target image are mapped. The Fig. 6 represents the final registered image and the Fig. 7 represents the area of tumor detected in brain.

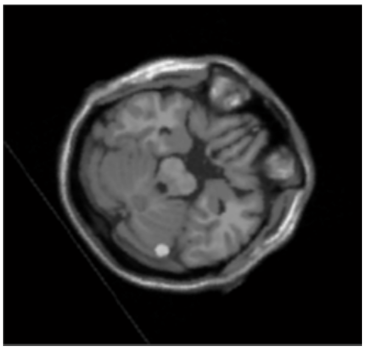


Fig. 8(a) T1 Weighted Image

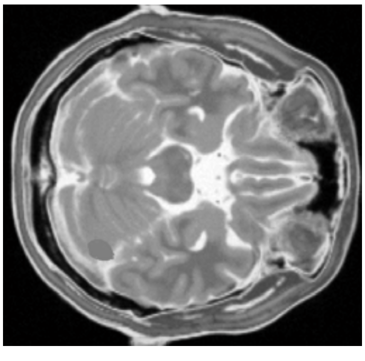


Fig. 8(b) T2 Weighted Image

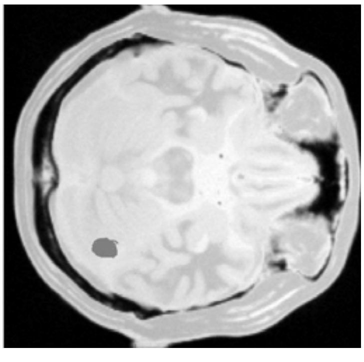


Fig. 8(c) PD Image

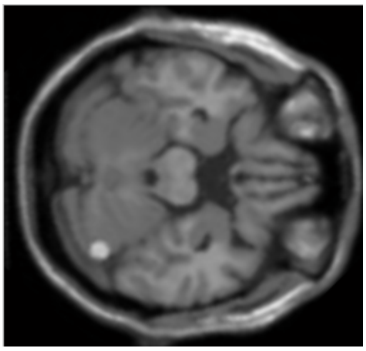


Fig. 9(a) Registered Image

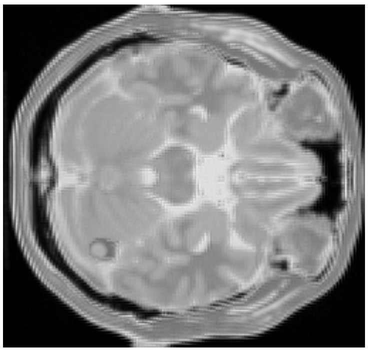


Fig. 9(b) Fused Image

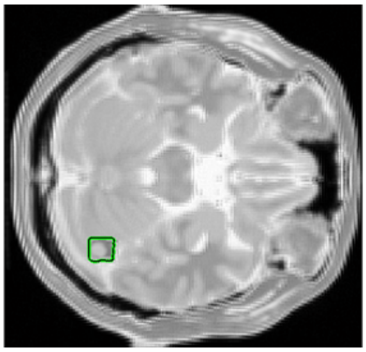


Fig. 9(c) Segmented Image

Fig. 8(a), Fig. 8(b) and Fig. 8(c) are the T1 weighted, T2 weighted and PD MRI images respectively, here T1 image is registered using proposed algorithm, the registered image is as shown in Fig. 9(a), Fig. 9(b) shows fused information of T1 weighted, T2 weighted and PD image respectively, here image is fused in spatial domain by using average fusion rule. Similarly Fig. 9(c) shows the segmented image using region growing algorithm. In our approach T2 weighted image is taken as reference image, T1 weighted image is mapped with T2 weighted image for registration. The table1 shows the comparison between the existing and proposed algorithm and methodology.

TABLE 1 : EXISTING AND PROPOSED ALGORITHM PRESENTATION.

| | **Algorithms** | **Presentation** |
|---|---|---|
| **Existing** | Graph based image registration and segmentation [13] | Prior knowledge is necessary |
| **Existing** | Combination of k-means and fuzzy C-means [11] , [12] | Better accuracy, but uses two segmentation algorithm, so computation time is more |
| **Proposed** | Enhanced Contourlet Edge based Registration + Region Growing | Detail Segmentation, low computation time |

## IV. CONCLUSION

The target image is different in angle and size compare to the source image. It is registered to the standard image using pyramidal directional filter bank which is combination of LP and DFB of contourlet transform. During image registration, Mutual Information as similarity measure is evaluated. Mutual Information technique and the contourlet-based edge extraction method are proposed for the multimodal image registration. MI technique has become a important and standard reference, mainly in medical imaging. It is considered with other like feature methods to get more gain with higher reliability, accuracy and robustness. Here it is combined with the contourlet transform. It is observed that as it can extract fine, accurate and continuous edges from the registered images, it can be effectively used in the feature extraction step of registration applications. Region growing algorithm is used to detect the tumor boundary after fusing the registered information. To increase accuracy, features of image can be extracted followed by Mutual Information as similarity measure.

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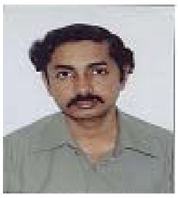

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