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A Novel Approach for Segmentation of Brain Image using a Multiscale Transform and a Region Based Active Contour

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ABSTRACT

Over the Past decade Medical Image segmentation is one of the most challenging and focused topic for intensive research in interdisciplinary areas of Image processing and computer vision. Segmentation is the process of automatic or semi-automatic detection of boundaries [5]. In this paper, we implement a novel unsupervised method for segmenting MRI brain Images based on multiresolution transforms and region based active contour. Application of multiscale, multiresolution methods with active contour is most interesting research topic in image segmentation [6].This new application makes segmentation algorithms more economical for computation.

Keywords: Multiscale and Multiresolution Transform, Chanvese active contour, Curvelet transform

1 Introduction

Segmentation is a fundamental operation on Medical image Analysis. Segmentation effectively partitions the image into homogeneous (segments) groups of common feature vectors that comprises gray levels, motion, texture etc. Boundary detection is an integral part of this process since it helps to identify the individual segments themselves. In this paper we propose an integrated segmentation approach that combines a gradient based Active contour method and multiscale Curvelet transform which is a sparsifying transform method to resolve the problem of intensity inhomogenity of Medical images, to reduce the computational cost and enhance the search for the global minimum. This proposed method promises to recognize weak edges and strong noises. This method was developed based on the inspired ideas of multiresolution wavelet transform hybrid with Active contour approaches. Curvelet is multidirectional, multiscale geometric wavelet transform [21]. Curvelet transform is relatively new multiresolution [20] analysis technique for sparse coding [optimal sparse representation [23] of objects and edges]. Curvelet produces the edge map of objects by Curvelet thresholding instead of simple gradient methods. In addition to this we also use the Mumford-Shah model based Chanvese active contour method for efficient image segmentation [22]. The Chanvese active contour is also a geometric active contour. Region based active contour model (ACM) utilizes the objective and the background regions statistically to find optimum energy. Due to which advantages over edge based ACMs, Region based ACMs are more popular for their robustness for image with weak

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edges or without edges. The Chanvese (CV) model is one of the most popular region based models [10]. In this paper we use a region based active contour method which ignores edges completely ("Active Contours without Edges" method by Chan and Vese [23]). Active contour models (ACMs) based segmentation methods have gained popularity due to their sub pixel accuracy as they provide closed and smooth edges.

2 Literature Survey

Curvelet transform is typically applicable in Medical image analysis for detecting intrinsic geometric curve like structures that forms a large portion of the medical images [15].Curvelet transform was initially introduced by Candes and Donoho[16]. Curvelet transform decompose the image into sub bands and separate the object into a series of disjoint scales. Curvelet thresholding is implemented for denoising[17,18,19], which proves efficient than gradient methods for recognize edges weak edges and as well as strong noises. A higher Curvelet coefficient corresponds to a stronger edge and the noise corresponds to a smaller coefficient. So by choosing Proper threshold, we retain the bigger coefficient and abandon the smaller coefficient to achieve the image denoising. Active contours are a catch-all name for methods that find the curve that best separates objects in an image. This is known as segmentation [1]. The concept of Active contour (AC) models for segmentation the original model were initially proposed by Kass et al[13].This classical approach drives an initial contour towards the boundaries of the objects by minimizing an energy function whose minimum is obtained at the boundaries of the object(s). Chanvese active contours [26] establish the most robust and efficient method of image segmentation than the classical methods of histogram, thresholding, gradient based methods etc. Chanvese method of segmentation is a special case of Mumford-Shah functional model. This method of segmentation is used widely in the medical imaging field, especially for the segmentation of the liver, brain, heart etc [29].The Chanvese model solves problems of curve evolution in the parametric active contour model and extends the application region of the active contour model. Chanvese [CV] model, also known as PC (piecewise constant) model, proposed in [25], is a simplified Mumford-Shah function. The model utilizes the global mean intensities of the interior and exterior regions of images. Thus, it has good segmentation result for the objects with weak or discrete boundaries but often has erroneous segmentation for images with intensity inhomogeneity. However, due to technical limitations or artifacts introduced by the object being imaged, intensity inhomogeneity often occurs in many medical images [31].

In section5 the level set formulation of the Chan-Vese model is described using a semi-implicit gradient descent.

Some of the limitations of Active contours are stated as follows:

1) The main drawback of these classical and traditional active contour models is that it depends on curve parameters, which cannot handle topology changes of the curve(s) automatically.
2) The curve evolution speed is very slow, as a result convergence is also slow and the level set formulation requires reinitialization at every step during evolution.
3) AC method has a great sensitivity to noise which may yield false segmentation results. Meanwhile, for noise images, the gradient descent flow requires much more expensive computation and iterations to force the active curve(s) to converge.

Combining a multiscale, multiresolution transform such as Curvelet transform with Active contour models can effectively and intuitively solve those problems of Noise inhomogenity [13]. Firstly, with the coarse-to-fine scale and small-to-big size strategies, the Activecontour models cost less expensive for computation because the rough segmentation results of the coarse scale maps can be taken as the initial contour of the following scale map. The multi-resolution strategy has more robust and strong ability to reduce the effect caused by noise [14].Wu et al., (2000) [2] proposed a directional image force for active contours based on wavelet frames. The wavelet-based snakes are helpful for noise suppression. Mignotte and Meunier (2001),[3]presented a multiscale approach for deformable contour optimization relying on a multigrid coarse-to-fine relaxation algorithm. Liu and Hwang (2003),[8]proposed an integrated wavelet-based snake model for segmentation and tracking based on the coarse-to-fine strategy. Bresson et al., (2006)[9] applied linear scale space into the parametric snake model. In this paper a Curvelet transform based geometric active contour is proposed for image segmentation of multiple objects. Curvelet denoising [17, 18] with proper threshold is superior to gradient methods as it promisingly recognize the weak edges and robust for strong noises. Alvino et al., [2005] have proposed a research thesis on novel multiscale active contour methods to several problems in computer vision, especially in simultaneous segmentation and reconstruction of tomography images [10].Multiscale image transforms like wavelets provide a directional image force for active contours, applying multiscale methods to snakes is one of the hot topics in image segmentation [11].

3 Methodology

3.1 Curvelet Multiscale transform for Image segmentation

FDCT can be implemented in two ways. First method is based on unequally spaced fast Fourier transform (USFFT) and the second is based on the Wrapping of specially selected Fourier samples. Both FDCT's differ by spatial grid used to translate Curvelet at each scale and angle and both FDCTs run in O (n2 log n).It is efficient for those images that display curve punctuated smoothness.

Fast Discrete Curvelet transform (FDCT) [24] takes as input a Cartesian grid of the form 0 , and outputs a collection of coefficients C^D (j, l, k) defined by where are digital Curvelet waveforms which preserve the listed properties of the continuous curvelet.

For a Cartesian array f$[n_{1,}n_2]$, where $0 \leqslant n \leqslant n_{1,}$ and $0 \leqslant n \leqslant n_{2,}$ and $n_{1,}n_2$ are dimensions of the array collection.

Curvelet coefficients C^D (j,l,k) indexed by a scale j, an orientation l and spatial location parameters k and is given by

$$C^D(j,k,l) = \sum_{n_1,n_2} f(n_{1,}n_2)\emptyset^D_{j,l,k}(n_1, n_2)$$

$$f(n_{1,}n_2), 0 \leq n_{1,}n_2 < n, 0$$

$\emptyset^D_{j,l,k}(n_1, n_2)$ is the digital curvelet waveform. Eqn [1] This is a part of Reiz representation.

Curvelet transform = IFFT [FFT (Curvelet) x FFT (Image)], and the product from the multiplication is a wedge.

Fast discrete curvelet transform via frequency wrapping is obtained from the following steps:

1. Apply the 2D fast Fourier transform (FFT) and obtain Fourier samples f^ [n1,n2], where −n/2 ⩽n1, n2< n/2.

2. For each scale j and angle l obtain Ũj, ℓ [n1, n2] f^ [n1, n2] by forming the product with Cartesian window

3. Wrap this product around the origin f`j,ℓ[n1, n2]=W(Ũj,ℓf^)[n1,n2] where the range for n1 and n2 is now 0 ⩽ n1< L1,j and 0 ⩽n2< L2,j and θ in the range (- π /4 , π /4).

4. Apply the inverse 2D FFT to each and hence collecting the discrete coefficients f`j,ℓ hence collecting the discrete coefficients CD(j, ℓ, k)[1].The software package CurveLab is used in implementing the Curvelet transform.

3.2 Mumford and Shah Minimization problem

The **Mumford–Shah functional** is a functional that is used to establish an optimality criterion for segmenting an image into sub-regions. An image is modeled as a piecewise-smooth function. The functional penalizes the distance between the model and the input image, by minimizing the functional one may compute the best image segmentation. The functional was proposed by mathematicians David Mumford and Jayant Shah in 1989[27].The Mumford-Shah model is an important variational image segmentation model. A popular multiphase level set approach, the Chan-Vese model [25, 30], was developed for this model by representing the phases by several overlapping level set functions. ChanVese approach involves geometric active contour model (based upon Mumford -Shah Functional). The model begins with a contour in the image plane defining an initial segmentation and then contour is evolved according to evolution equation. The basis of Chanvese algorithm is a Fitting Energy Functional [26, 28]. The goal of algorithm is to minimize this fitting energy for a given image and corresponding will define segmentation.

For any given image u_0 a decomposition $\Omega_i$of Ω and an optimal piecewise smooth approximation u of u_0 such that u varies smoothly within each $\Omega_1$and rapidly or discontinuously across the boundaries of Ω_i

To solve this problem, Mumford and Shah (1989) proposed the following minimization problem;

$$\inf\left\{F^{MS}(u,C) = \int_{\Omega}(u-u_0)^2 dxdy + \mu\int_{\frac{\Omega}{C}}|\nabla u|^2\ dxxy + v|C|\right\}$$

A reduced case of the model is obtained by restricting the segmented image u to piecewise constant function, i.e. $u = \text{constant } c_i$

Inside each connected component $\Omega_{i.}$.This problem is called “Minimal Partition problem” and its functional is

$$E^{MS}(u,C) = \sum_i \int_\Omega (u - c_i)^2\,dxdy + v|C|$$

It is easy to see that, for a fixed C, the energy from above is minimized in the variables c_i by setting

$$c_i = \text{mean}(u_0)\text{in}\Omega_i$$

3.2.1 Levelset curve formulation [Lipschitz function]:Ω→R

The Levelset curve evolution is explained in [29],

$$C = \{(x,y)|\Phi(x,y) = 0\}$$

$$\begin{cases} C = \partial\omega = \{(x,y)\}\epsilon\Omega : \Phi(x,y) = 0\} \\ \text{inside}(c_1) = \omega = \{(x,y)\epsilon\Omega : \Phi(x,y) > 0\} \\ \text{outside}(c_2) = \omega = \{(x,y)\epsilon\Omega : \Phi(x,y) < 0\} \end{cases}$$

Thus

$$F(c_1, c_2, C) = \int_{\Omega_1=\omega} (u_0(x,y) - c_1)^2 H(\Phi)dxdy \ + \int_{\Omega_1=\Omega-\omega} (u_0(x,y) - c_2)^2(1 - H(\Phi))dxdy + v\int_\Omega |\nabla H(\Phi)|$$

Where $H(.)$ is Heaviside function and $u_0(x,y)$ is the input image. This minimization problem is solved by taking the Euler-Lagrange equations and updating the level set.

In order to reach the minimum of F, we find the derivatives of F and set them to zero

From Euler-lagrange equation we therefore update $c_1 \text{and } c_2$ and Φ recursively.

$$\begin{cases} c_1(\Phi) = \dfrac{\int_\Omega (u_0(x,y)H(\Phi(t,x,y))dxdy}{\int_\Omega H(\Phi(t,x,y))dxdy} \\ c_2(\Phi) = \dfrac{\int_\Omega (u_0(x,y)(1 - H(\Phi(t,x,y)))dxdy}{\int_\Omega (1 - H(\Phi(t,x,y)))dxdy} \end{cases}$$

$$\frac{\partial\Phi}{\partial t} = \delta(\Phi)[v\text{div}(\frac{\nabla\Phi}{|\nabla\Phi|} - (u_0 - c_1)^2 - (u_0 - c_2)^2]$$

Where $\delta(.)$ is the Dirac function.

3.2.2 The Chanvese active contour without edges

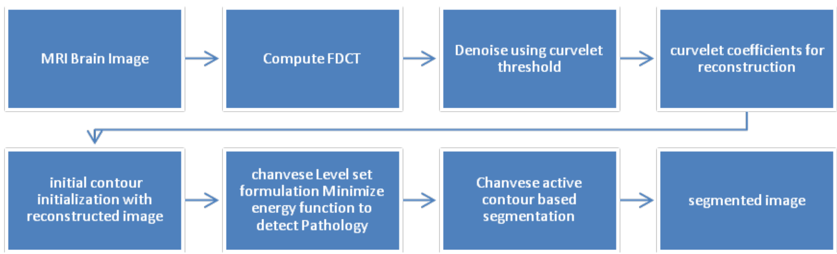
By the Mumford Functional for "Minimal partition problem" and by the given curve $C = \partial\omega$, with $\omega \subset \Omega$ an open subset, and two unknown constants $c_1$and

c_2,denoting $\Omega_1 = \omega$,$\Omega_2 = \Omega - \omega$. Chanvese proposed to minimize the energy with respect to c_1, c_2 and C

$$F(c_1,c_2,C) = \int_{\Omega_1=\omega} (u_0(x,y) - c_1)^2 dxdy \; + \int_{\Omega_1=\Omega-\omega} (u_0(x,y) - c_2)^2 dxdy \; + v|C|$$

to detect objects in a given image based on techniques of curve evolution, Mumford–Shah functional for segmentation and level sets.

3.3 8. Our Proposed method



To extract the desired regions of interest [ROI], the proposed algorithm operates by decomposing the enhanced image into different frequency bands. The Fast Discrete Curvelet Transform (FDCT) is applied this allows a sparse representation of objects in an image. With proper threshold, Curvelet denoising is performed on the image. The image is then reconstructed with curvelet coefficients after threshold and denoising. Thus this reconstructed Curvelet output image is used to initialize the Chanvese region based active contour model. We used the two phases and multiphase Chanvese active contour model that utilizes the global mean intensities of the interior and exterior regions of images, and provide good segmentation for the objects with weak or discrete boundaries.

4 Results

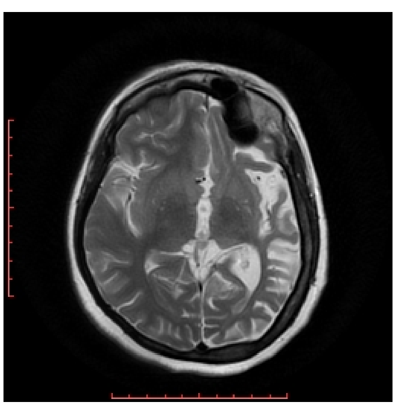


Fig 4.1) Brain MRI Image

Fig 4.2) Curvelet denoised and fused output image

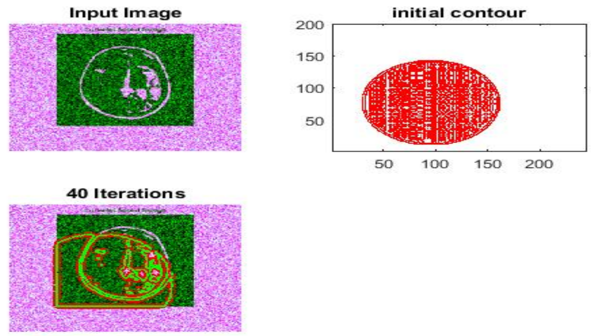


Fig 4.3) Chanvese active contour segmentation initialized with Curvelet output

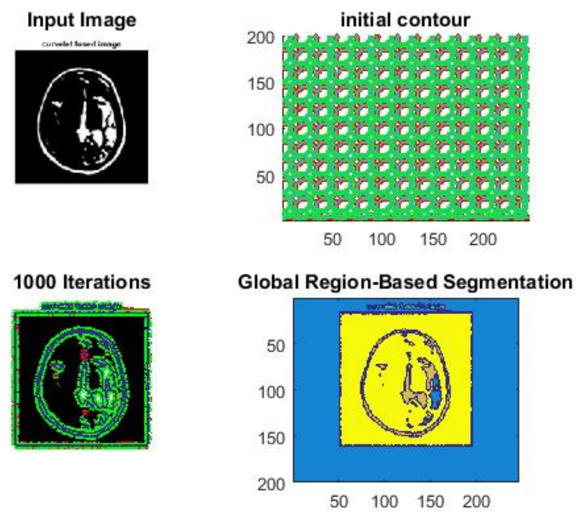


Fig 4.4) Integrated Multiscale and region based segmentation output.

Fig 4.1 shows the MRI image of human brain, which is then, analyzed using multiscale and multiresolution strategies using Curvelet transform. The Curvelet coefficients with suitable thresholding are reconstructed and denoised to produce the output image in **Fig 4.2**. The output image in **Fig 4.2** is then initialized and segmented using Chanvese active contour in two phases, with noise removal at intermediate stages **Fig 4.3**. Finally we get the segmented output as shown **Fig 4.4** which shows the Pathological region highlighted in bluish patch, the segmented output.

5 Discussion and Conclusion

Application of Multiscale methods with Active contour model for image segmentation is an active research area. In this paper a combination of Multiscale Curvelet transform and Chanvese region based active contour is proposed for detecting the desired ROI from MRI Brain Images. The Curvelet transform is a multi scale transform with better directional sensitivity .It helps to extract the image detail at various scales and directions according to the features of interest to be extracted. Integrating a multiscale , multiresolution transform such as Curvelet transform with Active contour models can effectively and intuitively solve those problems of Noise inhomogenity [13].The proposed Multiscale active contour segmentation model uses the entire scale space, to introduce the geometry of multiscale images in the segmentation process. The extracted multiscale structures will efficiently improve the robustness and the performance of standard shape analysis segmentation techniques such as shape recognition and shape registration and is able to extract convex and concave object based on coarse-to-fine scale and small-to-big size strategies. The active contour models cost less expensive for computation because the rough segmentation results of the coarse scale maps can be taken as the initial contour scale map. The multi-resolution strategy is more robust to reduce the effect caused by noise. The segmented images show improved accuracy and precision. Further the research is open to implement other variational levelset Active contours for efficient segmentation.

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