MEDICAL IMAGE SEGMENTATION USING DEFORMABLE MODELS AND CONTOURLET TRANSFORM

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ABSTRACT

Multiresolution analysis is often used for image representation and processing because it can represent image at the split resolution and scale space. In multi-resolution analysis, an image is viewed at various levels of approximations or resolutions. In this paper, a novel medical image segmentation algorithm is proposed that combines Contourlet transform and deformable model. This method has a new energy formulation by representing the image with the coefficients of a Contourlet transform. This results fast and accurate convergence of the contour towards the object boundary. Medical image segmentation using Contourlet transforms has shown significant improvement towards the weak and blurred edges of the Magnetic Resonance Image (MRI). Also, the computational complexity is less compared to using traditional level sets and Variational level sets for medical image segmentation. The special property of the Contourlet transform is that, the directional information is preserved in each sub-band and is captured by computing its energy. This energy is capable of enhancing weak and complex boundaries in details. Further, due its directional image expansion property, smoothness along the contours of the medical image can be easily achieved. Performance of medical image segmentation algorithm using Contourlet transform and other hybrid models (Deformable models with Contourlet) is compared with other deformable models in terms of various performance measures.

Keywords: Segmentation, Contourlet Transform, MRI, Brain tumor, Deformable Models, Level Sets.

I. INTRODUCTION

Segmentation is nearly always the crux of any problem in computer assisted medical image computing. Image segmentation occurs as a fundamental early vision processing task in many important medical applications. Image segmentation is considered as the most difficult stage in digital image processing because the aim and implementation of segmentation are very much dependent on data types and applications. A large number of techniques and algorithms have been proposed in the literature [1], [2], [3], [4].

Medical image segmentation is the process of labeling each pixel or voxel in a medical image dataset to indicate its tissue type or anatomical structure. The labels that result from this process have a wide variety of applications in medical research and visualization. Segmentation of an anatomical structure from medical image amounts to identifying a region or boundary of an image corresponding to the desired structure. There is an immense array of scientific literature focusing on the task of medical image segmentation [5], [6], [7] and it has received significant attention, due to many practical applications of segmentation results. By making use of medical image segmentation approaches accurate, repeatable, quantitative data must be efficiently extracted in order to support the spectrum of biomedical investigations and clinical activities, from diagnosis, to radiotherapy to surgery. Many different image segmentation algorithms have been developed in the past several decades but it remains a complex and challenging task.

Medical image segmentation algorithm could be used to recognize pathologies, such as tumors, by first eliminating the recognizable neuro-anatomical structures. Any remaining unrecognized feature is likely to be pathological. Furthermore, the algorithm could also be used in determining the particular disease from a set of
differential diagnoses. Location is very important because the evolution of the disease, its cause, and the available treatment options depends on the affected anatomical structure in which the pathology lies.

The watershed transform used in hybrid model [8], [9] relying mostly on image gradients, small fluctuations in the image grey values due to the noise produce spurious gradients, which causes over segmentation and degrade the output of the watershed transform. Also, low-contrast edges produce gradients with small magnitudes, which may cause different regions to be erroneously merged. The reason behind this is that, watershed algorithm segments even small scale details in the image. Therefore, many morphological filters are often designed to smooth noisy gray-level images by a determined composition of opening and closing with a given structuring element. These limitations can be addressed by using multiresolution methods [10], [11]. In these techniques, contour attraction towards the weak and blurred edges can be easily achieved without any re-initialization. Also, the computational complexity is less compared to traditional level sets and Variational level sets [12], [13], [14], [15].

There are particular class of multiscale segmentation technique based on wavelets relies on multiscale representations of images. Such methods are typically based on image transformations that change image resolution, being able to segment objects of different sizes. In general small details are detected in higher resolution images, while larger objects are segmented in coarser images. The advantages of using wavelets are that, it allows an approximation of the tumor boundaries by increasing or decreasing the number of wavelets coefficients. Further, the wavelet decomposition is a complete representation, since it allows a perfect reconstruction of the original image [16], [17]. However, wavelets are good at isolating the discontinuities at edge points of an image, but cannot see the smoothness along the contours. Further, wavelets can capture only limited directional information like horizontal, vertical and diagonal. So these limitations restrict using wavelets for specific applications.

To overcome these limitations, multiscale and directional representations, which can capture the intrinsic geometrical structures such as smooth contours in medical images, have been developed [18]. The main drawback in these methods is that there is no flexibility in selection of different number and directions at each scale. To overcome this deficiency, Do and Vetterli [19] proposed the Contourlet Transform (CT) based on 2-D multiscale and directional filter bank that can deal efficiently with images having smooth contours which are common in medical images. The special property of the Contourlet transform is that, the directional information is preserved in each sub-band and is captured by computing its energy. This energy is capable of enhancing weak and complex boundaries in details. Further, due its directional image expansion property, smoothness along the contours can be easily achieved. Hybrid models (combining watershed and deformable models) are computationally efficient but they are poor in convergence, due to the lack of details along the edges of the object boundaries. However, hybrid model (combining Contourlet with deformable models) is superior in terms of convergence.

The remaining structure of this paper is arranged as follows. Review of Contourlet transforms is presented in section II. The proposed hybrid algorithm for medical image segmentation using Contourlet transform is presented in section III. Experimental results and comparison of the proposed algorithm with the existing algorithms are presented in section IV. Concluding remarks are given in section V.

II. REVIEW OF CONTOURLET TRANSFORM

Contourlet transform is an extension of the wavelet transform which uses multi scale and directional filter banks. Although the wavelet transform is powerful in representing images containing smooth areas separated with edges. It cannot perform well when the edges are smooth curves. The Contourlet transform is one of the new geometrical image transforms, which represents images containing contours and textures. The Contourlet transform effectively captures smooth contours images that are the dominant feature in natural images. The main difference between Contourlet and other multi scale directional systems is that the Contourlet transform allows for different and flexible number of directions at each scale, while achieving nearly critical sampling. Candes and Donoho showed that wavelets perform well for objects with point singularities in 1-D and 2-D. Orthogonal wavelets capture only horizontally, vertically, and diagonally directed discontinuities. These orientations may not preserve enough directional information in medical images. Ridgelets analysis, on the other hand, is an appropriate transform to catch radial directional details in frequency domain. Ridgelets are very effective in detecting linear radial structures, but those structures are not dominant in medical images.

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An extension of Ridgelets transform is the Curvelets transform. Curvelets transform overcomes the directionality lack of 2-D wavelets by geometrically representing smoothness of contours. But, theoretically there are no significant differences in the time performance in compared with wavelets transform. Also, Curvelets are highly anisotropic at fine scales, but Curvelets construction is simple in continuous domain and complex in discrete domain. Further, they are slow as compared to Contourlet transforms. Do and Vetterli [19] constructed a discrete domain multiresolution and multidirectional expansion using non-separable filter banks to obtain sparse expansions for typical images having smooth contours. In this double filter bank, the Laplacian pyramid (LP) is first used to capture the point discontinuities, followed by a directional filter bank (DFB) to link point discontinuities into linear structures. The overall result is an image expansion using basic elements like contour segments, named Contourlet. In particular, Contourlet have elongated supports at various scales, directions and aspect ratios. Making use of these efficient properties of Contourlet transform, a new segmentation algorithm is proposed. In this algorithm Contourlet represents features of medical images efficiently compared to other transforms. Figure 1 shows a block diagram of the Contourlet transform.

It consists of two steps: Sub-bands decomposition and directional transform. A Laplacian pyramid (LP) is first used to capture point discontinuities, then followed by a directional filter bank (DFB) to link point discontinuity into linear structure.

![Figure 1. Block diagram of the Contourlet transform. The image is first decomposed into sub bands through Laplacian Pyramid and then each band pass/ detail image is analyzed by the directional filter banks (Do and Vetterli et al., 2005).](image1)

First stage is low pass decomposition and second stage is DFB decomposition. The LP decomposition at each step generates a sampled low pass version of the original and the difference between the original and the prediction, resulting in a band pass image. Figure 2 shows an example of the Contourlet decomposition by considering an input MR T1 weighted image. This image is decomposed into four levels by the DFB. Top most band shown in figure 2, is a low pass image. For LP directions, $n'$ is used. At each successive level the number of directional sub-bands is 4, 4, 8 and 16 respectively. For both pyramidal filter and directional filter the pkva filter is used.

![Figure 2. Four levels Contourlet decomposition of the T1 weighted MR image data tumor 01. Small coefficients are shown in black while large coefficients are shown in white.](image2)
Proposed Hybrid Algorithm using Contourlet Transform

In the proposed algorithm level set is used in conjunction with the Contourlet transform for the segmentation of tumor boundary. The reason using level set in this method is that, Snake models cannot handle topological changes and it has a tendency to produce degenerate contours or self-intersections. The treatment of the proposed algorithm is divided into two stages. The first stage is used to compute the energy of the Contourlet transform decomposed MR image. The second stage corresponds to integration of this energy using deformable models. In the first stage Contourlet transform is applied to the given raw MR image. Pyramidal Directional Filter Bank (PDFB), which decomposes images into directional sub-bands at multiple scales. The CT decomposes the original image into four sub-bands. The approximation sub-band preserves the information of the original image, and the detail sub-bands capture the intensity variations in all the directions. After CT is applied on the image, Contourlet coefficients from the detail sub-bands of all the decomposition levels are used to formulate the energy coefficients. The Standard Deviation ($\sigma_k$) and/or energy ($E_k$) of the CT decomposed image on each directional sub-band can be calculated by using,

$$\sigma_k = \frac{1}{NN} \sum_{i=1}^{N} \sum_{j=1}^{N} (W_k(i,j) - \mu_k)^2$$

(1)

$$E_k = \frac{1}{NN} \sum_{i=1}^{N} \sum_{j=1}^{N} W_k(i,j)^2$$

(2)

where, $W_k$ is the coefficients of $K^{th}$ Contourlet decomposed sub-band, $\mu_k$ is the mean value of $K^{th}$ sub-band and $NN$ is the Contourlet decomposed sub-band. The resulting Standard deviation, energy and SD segmented with energy feature vectors are given as follows.

$$\mathbf{f} = [\sigma_1, \sigma_2, \sigma_3, ..., \sigma_n, E_2, E_3, ..., E_n]$$

(3)

where, $n$ is the number of directional sub-bands. The Contourlet energy of each pixel is computed by taking the total of the average values in all directions. Each of the Contourlet energy value represents the respective pixel’s intensity variation information. The final Contourlet energies of all the pixels in the image produce a Contourlet energy map that shows the various intensity variations present in the image.

In the second stage Contourlet energy computed from the first phase will be used to infer the statistical information of the pixels in the image. These Contourlet energy values are then formulated into the region based level set method. Assume that an original image $f(x,y)$ contains two structures i.e., desired object and the background. The proposed algorithm segments object from the background with the contour $C$ separating these two structures. In level set a surface $\phi$ is evolving instead of front $C$. In level set method the contour $C(s)$ is represented by using an implicit function $\phi(x,y,t)$ and the front is then defined implicitly as the zero level set $\phi = 0$. Therefore the segmented region will be the pixels where this surface is above zero. Here, surface $\phi$ whose zero level set curve aligns with the edges in the object boundary. The proposed method minimizes an energy function based on this surface $\phi$. Then the total energy function for the hybrid model can be formulated as

$$E_{hybrid}(\phi) = E_{internal}(\phi) + E_{image}(\phi)$$

(4)

Now energy function is defined using Contourlet coefficients and surface $\phi$ of the level set and the total energy function is minimized by using standard iterative technique. At each iteration search direction and a distance to move is chosen. Here, a gradient energy is used as search direction. Simple second order energy functional is used to calculate the gradient and length. Before defining internal energy and external energy, represent the original image $f(x,y)$ and surface $\phi(x,y)$ by placing the values in the corresponding column vectors as $f_\phi$ for the original image and $f_\phi$ for the surface respectively. Then find matrices $M_f$ and $M_e$ corresponding to forward
and reverse transform respectively. Then \( m_\phi = M_f f_\phi \) and \( f_\phi = M_f m_\phi \), where, \( m_\phi \) is the column vector in which, all contourlet energy coefficients are stacked. To calculate internal energy, at each iteration of the algorithm estimate the contour by defining, a surface \( f_\phi \) to be +1 inside the contour and −1 outside the contour. Then calculate the smoothed contourlet transform of this surface as \( m_\phi = WM_f \), where \( W \) represents the diagonal matrix which represents low pass coefficients, setting all high pass coefficients to zero. Now the internal energy is

\[
E_{\text{internal}} = (m_\phi - m_x)' A^{-2} (m_\phi - m_x)
\]

(5)

where, \( A \) is the diagonal weighing matrix for the coefficients. The image energy \( E_{\text{image}} \) relative to the surface \( f_r \) is given by,

\[
E_{\text{image}} = \|r (m_\phi - f_r)\|^2
\]

(6)

where, \( r \) is a diagonal matrix, represents the value at \( f_I(x,y) \). Now the surface, \( f_r \) is designed to have a level set curve that is close to the previous contour estimate.

For better aligned with the edges in the object boundary the noise in the image must be removed. This can be done by considering the original image data vector \( f_I \) and the surface vector \( f_\phi \) using de-noise technique (Jung, 2007). Then the new Contourlet coefficients after de-noising results the new level set curve \( f_r \).

Now the total energy functional based on newly defined internal energy and image energy is as follows.

\[
E_{\text{hybrid}}(\phi) = E_{\text{internal}}(\phi) + E_{\text{image}}(\phi)
\]

(7)

here, \( A \) is the diagonal vector, \( \tau \) is the diagonal vector of entries either 1 or 0. The defined energy function \( E(\phi)_{\text{hybrid}} \) is represented using the Euler Lagrange equation with fixed parameters. To implement the hybrid model energy function, the time step in that equation is replaced by number of iteration of the contour. The contour is updated based on the energy and initialize \( u_\phi \), each iteration calculate a change of Contourlet coefficients. The search direction is given by evaluating \( \nabla u_\phi E_{\text{hybrid}} \) at the current value for \( u_\phi \). The final task is to determine the optimum step size \( \beta \). The new scaled Contourlet coefficients will be given by \( u_\phi - \beta \nabla u_\phi E_{\text{hybrid}} \). The energy for surfaces in this direction will have a simple quadratic form which can be solved to show that the minimum energy is given by a step size. Multiresolution methods viz., wavelet transforms have fixed number of directions and also they are inefficient to capture smooth contours which are common in MR images. So the combination of Contourlet transform and the level set methods yields better results as compared to multiresolution segmentation using wavelets.

### III. EXPERIMENTAL RESULTS

In order to demonstrate the strengths of the proposed algorithm based on Contourlet transform, several experiments are performed on the MR images of the brain. The proposed algorithm is implemented using Matlab. Figure 3 demonstrates the segmentation results of the proposed method with the existing methods visually for the data set tumor 1.
Figure 3. Segmentation results of wavelets and Contourlet methods for tumor 01. (a) original image, (b) ground truth, (c) snake method, (d) extracted tumor area, (e) GAC method, (f) extracted tumor area, (g) GVF method, (h) extracted tumor area, (i) enhanced image by wavelet (j) extracted boundaries of the enhanced image, (k) final segmentation using wavelet-watershed, (l) enhanced image by Contourlet, (m) segmentation by the proposed method and (n) extracted tumor area.

In these experiments, the performance of the proposed algorithm is compared by applying Contourlet to traditional snakes, GAC, GVF methods. The visual results of the proposed method show that, the proximity of the contour towards the object boundary is more accurate than the other methods. Figures 3 (i), (j) & (k) demonstrates the results of the wavelet based segmentation algorithm. In this method, the curve representing the object of interest cannot arrive at the boundary in the concavity of the object. Figures 3 (l), (m) and (n) demonstrate the performance of the proposed Contourlet transform. Figure 4 illustrates the comparative analysis of the proposed method and the existing segmentation techniques.

![Performance measures chart for tumor 1](chart.png)

Figure 4. Comparative analysis of the proposed method with the existing method.
IV. CONCLUSION

In this work a novel segmentation framework based on Contourlet transform is proposed. This method resulted in significant improvement in accuracy for segmenting complex MR images of brain. In the proposed algorithm, Contourlet transform is introduced to calculate the image features as energy coefficients by decomposing the given input image in Contourlet domain. These energy coefficients are integrated in the region based active contours such as level sets to guide this energy towards the desired object boundary. The extensive experiments on MR images demonstrated the advantages of the proposed method over the classical deformable models such as snakes, GAC, GVF, Level sets and Variational level sets. The superiority of the proposed algorithm is compared with the various types of deformable models. Finally, the performance of the proposed method is evaluated by visual comparison and measurement of sensitivity, specificity and segmentation accuracy. These performance measures proven that, the proposed method is an accurate method for segmenting the tumor boundary even in the presence of smooth and discontinues edges present in medical images.

REFERENCES