Hybrid Model For Analysing Medical Image Using Fuzzy Segmentation, Self-Organizing Map and Localizing Region-Based Active Contours Algorithms

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Abstract:
In this paper, we are presenting hybrid methods for analysis of radiological image, such as CT, MRI, etc., to get the interested area from the medical image. This approach integrates fuzzy segmentation methods (FSM), localizing region-based active contours (LRBAC) and self-organizing map (SOM). Such integration of these methods is useful in focusing region of interest in medical images and optimizing the result. Firstly, we use fuzzy methods to get an initial segmentation result. Then we use LBARC and SOM to get smooth, accurate and optimized result. This hybrid approach is automated, since the whole segmentation procedure doesn’t need much manual intervention, except the initial seed position selection for fuzzy connectedness segmentation.

Keywords: Fuzzy segmentation method (FSM), localizing region-based active contours (LRBAC), self-organizing map (SOM).

1. Introduction

Segmentation involves dividing an image into distinct classes or types. For example, researchers may segment the brain into three classes: gray matter, white matter, and cerebrospinal fluid. There are two types of segmentation: hard and soft, or fuzzy[4]. In Hard segmentation a pixel is assigned to only one class. In medical images, absolute classification of a pixel is often not possible because of partial volume effects where multiple tissues contribute to a pixel or because a voxel causes intensity blurring across boundaries [5]. Soft or fuzzy segmentation allows for the uncertainty in the location of object boundaries. In fuzzy segmentation, a membership function exists for each class at every pixel location. At each pixel location a class membership function has the value of zero if the pixel does not belong to the class. At each pixel location a class membership function has a value of 1 if the pixel belongs, with absolute certainty, to the class. Membership functions can vary from 0 to 1, with the constraint that at any pixel location the sum of the membership functions of all the classes must be 1. The fuzzy membership function reflects the similarity between the data value at that pixel and the value of the class centroid. As a pixel data value becomes closer to the class centroid, the class membership function approaches unity[1]. The basic idea of localizing region-based active contours (LRBAC) is to allow a contour to deform so as to minimize a given energy functional in order to produce the desired segmentation. There exists main categories for active contours: edge-based and region-based. Edge-based active contour models utilize image gradients in order to identify object boundaries, e.g., [10], [11].
This type of highly localized image information is adequate in some situations, but has been found to be very sensitive to image noise and highly dependent on initial curve placement [2]. One benefit of this type of flow is the fact that no global constraints are placed on the image. Thus, the foreground and background can be heterogeneous and a correct segmentation can still be achieved in certain cases.

Neural networks are one of the classification based segmentation methods [5]. They perform classification by a method that learns from data, instead of using a given rule set. They organize themselves in a data driven manner. Neural network methods attract more and more attentions for its abilities of self-learning, fault tolerance, and optimum search. In this paper, a novel MR images segmentation method is presented based on Hybrid self-organizing map (HSOM) neural network. HSOM is an unsupervised neural network that use competitive learning algorithm.

2. METHOD AND MODEL

A. The Fuzzy C-Means algorithm is an unsupervised method. That is, it works without the use of a specialized set of data for determining parameters of an algorithm. This algorithm, which allows for fuzzy segmentation based on fuzzy set theory, generalizes the K-Means algorithm[3]. The technique clusters data by iteratively computing a fuzzy membership function and mean value estimate for each tissue class. The algorithm uses Anisotropic Diffusion Filter. Anisotropic diffusion can be used to remove noise from digital images without blurring edges. Perona and Malik developed this powerful multistage smoothing and edge detection filter. This anisotropic diffusion filtering method is mathematically formulated as a diffusion process, and encourages smoothing within a region in preference to smoothing across the boundaries. In their filtering method the estimation about local image structure is guided by knowledge about the statistics of the noise degradation and the edge strengths [6]. The anisotropic diffusion is defined as

\[ \frac{\partial I}{\partial t} = \text{div} \ c(x, y, t) \nabla I = \nabla c, \nabla I + c(x, y, t) \Delta I \]  

(1)

Where \( \nabla \) denotes the gradient, \( \text{div} (\ldots) \) denotes the divergence operator and \( c(x,y,t) \) is the diffusion coefficient. The \( (x,y) \) represents spatial coordinates and \( t \) is used for enumerating iteration steps. I represent the intensity function of an image. \( c(x,y,t) \) controls the rate of diffusion and is usually chosen as a function of the image gradient so as to preserve edges in the image. This function \( c(x,y,t) \) is a monotonically decreasing function. This function diffuses within regions and does not affect region boundaries that are at locations of high gradients. The function for the diffusion coefficient is

\[ \nabla = 1 \ 1 + \nabla I \ k \ 2 \]  

(2)

The constant \( K \) controls the sensitivity to edges and is usually chosen experimentally or as a function of the noise in the image [7].

B. Stationary Wavelet Transform  The stationary wavelet transform (SWT) is an improvement of the discrete wavelet transform (DWT). It is designed to overcome the lack of translation-invariance of the DWT. The process of the SWT is very similar describing the DWT process. The only difference is that the SWT does not perform down-sampling after every filtering step, and instead up-samples the filters at every step which is shown in Fig.1. [8]. Since the outputs do not get down-sampled, the SWT produces two outputs with the same amount of coefficients as components in the input signal at each step. This gives a redundant result where no valuable information is lost, which can be necessary for sensitive data [9].

SWT is defined by Unser [10], for the characterization of texture properties at multiple scales using the wavelet transform. The multiresolution properties of the wavelet transform are beneficial for texture discrimination. It is proven that this translation-invariance representation constitutes a tight frame and it has a fast iterative algorithm. For application of
the decomposition, the filter used in decomposition is up sampled for each iterations using Equation (3) and convolved with the signal to obtain the sub signals of the next level using Equation (4), instead of applying down sampling process to the signal like in traditional transform methods.

\[ i+1 k = h ↑2ihi k \]

\[ gi+1 k = g ↑2igi k \]  (3)

Here the arrow marks \([.]↑m\) denotes the up sampling by a factor of m. The effects of one iteration means dilating the filters \(hi\) and \(gi\) by a factor of 2: \(si+1 k = hi+1 k si k\) \(di+1 k = gi+1 k si k\)  (4) Each proceeding step involves convolution with the basic filters \(h\) and \(g\) that are expanded by inserting appropriate number of zeros between filter taps. The complexity of this algorithm is proportional to the number of samples. The sub signals obtained from the SWT have the same length with the original signal and the results are translation invariant. Nonetheless they contain information of the middle frequency region which is very useful for segmenting images.

B. SOM (Self-Organizing Map) introduced by Kohonen [11], is an unsupervised learning neural network. They perform classification by a method that learns from data, instead of using a given rule set. SOM projects a high dimensional space to a one or two dimensional discrete lattice of neuron units. Each node of the map is defined by a vector \(W_{im}\) as shown in below diagram [fig 1] and these elements are adjusted during the training. An important feature of this neural network is its ability to process noisy data. The map preserves topological relationships between inputs in a way that neighbouring inputs in the input space are mapped to neighbouring neurons in the map space [12].

![Fig 1: schematic representation of self-organized map](image)

C. Localizing region-based active contours model always need specified training followed by a complex matching process of shifting and stretching transformations [9]. Based on the LCV model, we utilized this initial contour as a simple and effective shape constraint to avoid boundary leakage and excessive contraction during the segmentation process. This shape constraint was incorporated into the level set framework of the LCV model, and accurate segmentation results were acquired in the experiments. Here, we call our proposed shape constrained localized region-based active contour model the SLCV model.
The basic idea is to add shape constraint energy to the process of separately calculating each point’s localized energy on the curve. The shape constraint energy is acquired by a function of the nearest distance between the point and the initial contour.

3. Experimental Analysis

We conducted experiments on a desktop with an Intel CPU of Core Dual-core E7500 2.93 GHz, 2 GB RAM, Windows XP 32-bit and Matlab 2012a. We first used synthetic images to test the effects of the shape constraint proposed in this work. When initializing contours using an ellipse on the synthesized images, we utilized a shape constraint so that the final segmentation would retain an approximately elliptical contour. However, without a shape constraint, common segmentation results will stall at clear edges and cannot maintain the true shape of the target. The experiment indicates that boundary leakage and excessive contraction will not occur in the segmentation of images with information loss or severe noise near the target region when a shape constraint is introduced to maintain the true shape of the target.

A. Setting the Parameters

In the equation (10), \( \mu \) and \( \beta \) are two important parameters. \( \mu \) decides the smoothness of the curve, and if \( \mu \) is too small, it will result in some independent points in the segmented image with substantial noise. Thus in HIFU ultrasound images with considerable noise, we usually choose a relatively large value for \( \mu \) as the weight of the regular term. \( \beta \) decides the value of the shape constraint forces in the segmentation. If its value is too large, the initial contour will evolve very little if at all; if it is too small, the proposed model will be degraded without shape constraint. In fact, \( \beta \) should be chosen according to the quality of the images to be segmented. It can be a relatively small value if the image has clear edges and little noise; if the opposite is true, \( \beta \) should be a relatively large value, thus enhancing the effect of the shape constraint. Meanwhile, the closer the initial contour is to the true contour of the target region, the larger \( \beta \) should be. In the experiments, we choose 0.2 for \( \mu \) and 0.5–0.9 for \( \beta \). The segmentation of HIFU ultrasound images of uterine fibroids because of the images’ quality and the uterine fibroids’ shape.

B. The Localizing Radius

As another important parameter, the localizing radius is separately discussed here because it decides localization, thereby affecting the final segmentation results. An improper localizing radius can produce incorrect results in regions with extensive noise. Figure 7 illustrates the effects of different localizing radii on segmentation results using the LCV and MSLCV models. In Figure 7(a) and Figure 7(d), the iteration was slow under a relatively small
localizing radius that led to incorrect results. Because of the shape constraint and multi-scale segmentation, the MSLCV model effectively reduced the problem of boundary leakage caused by the relatively large localizing radius while worsening the difficulty in evolving the contour when the localizing radius was relatively small. Thus, it is of great importance for segmentation accuracy and efficiency to choose a suitable localizing radius.

Figure 2. Effects of different localizing radii on the segmentation results.

The first row and the second row present the segmentation results with different localizing radii using the LCV model and the MSLCV model, respectively. The green curves are manual segmentation results by the specialist, the red curves are the results from the experiments, and the yellow circles represent the size of localized regions formed by the localizing radius. The localizing radii of (a) and (d), (b) and (e), and (c) and (f) are 4, 20 and 45, respectively.

The localizing radius should be chosen according to the scale of the target region and the presence and proximity of surrounding noise, but they did not give a method for adaptive selection of the localizing radius. We do so by making use of well-initialized contours. Because difference of the size of the target region may be substantial, to automate the selection of the localizing radius, we connect the selection to the size of the well-initialized contour. We take a proportion of the sum of the difference between the maximum and minimum values on the $x$ axis and $y$ axis, respectively, of the initial contour in the image as an input parameter of the localizing radius’ adaptive selection function. For example, if we utilize an ellipse to initialize the contour, we take a proportion of the sum of the major and minor axes of the ellipse. The localizing radius’s adaptive selection function $R(X)$ is defined as:

\[
R(X) = k \left( \|x_{\text{max}} - x_{\text{min}}\| + \|y_{\text{max}} - y_{\text{min}}\| \right),
\]

where $k$ is a coefficient that controls the proportion, which is usually set as 0.25. $x_{\text{max}}$ and $y_{\text{max}}$ respectively, are the maximum values of the initial contour on the $x$ axis and $y$ axis, while $x_{\text{min}}$ and $y_{\text{min}}$ are the minimum values. Figure 8 demonstrates that the function $R(X)$ effectively avoids the problem of the localizing radius being too large or too small when the segmentation target is too large or too small. We set a range of 10 to 40 for the localizing radius according to the size of the uterine fibroids in the HIFU ultrasound images and experimental results to avoid the lack of evolution of the contour that occurs when the localizing radius is too small and the boundary leakage and greatly increased calculation time that occur when the localizing radius results is too large. In the multi-scale segmentation, we set a larger $k$ in the first segmentation to obtain a larger localized radius, faster convergence and weaker initialization sensitivity, and set a smaller $k$ on the second segmentation to reduce the calculation time.
The effect of the incorporated shape constraint relies on the initial contour. To reduce initialization sensitivity, we consider using a zero narrow band that is generated around the zero level set created by the initial contour. The shape constraint is ignored within the zero narrow bands. The width of the zero narrow band is represented by $2w$. Ignoring the constraint within the zero narrow band reduces the effect of the shape constraint around the initial contour and thus reduces the initialization sensitivity. In the multi-scale segmentation, for the first segmentation, we use the zero narrow bands to reduce the initialization sensitivity due to the manually initialized contour, while on the second segmentation; we do not use the zero narrow band because, the coarse contour has already been confirmed.

Conclusions

B. In this paper, an accurate and efficient multi-scale and shape constrained localized region-based active contour model, called the MSLCV model, has been proposed to perform semi-automatic segmentation of uterine fibroid in ultrasound images for HIFU therapy. By incorporating a new shape constraint into the localized region-based active contour, we have
obtained a more precise segmentation result, avoiding the problems of boundary leakage and excessive contraction due to the low SNR, weak boundaries and intensity inhomogeneity of HIFU ultrasound images. Further, to overcome the shortcomings of the large computation time and the time-consuming nature of the segmentation process in the localized region-based active contour model, we have proposed a multi-scale algorithm that greatly improves the segmentation efficiency. Meanwhile, to solve the problem of the selection of localizing radius and initialization sensitivity, we have discussed and analysed the adaptive selection of the localizing radius and the formation of a zero narrow band.

Conclusions & Future Work

In this paper, an accurate and efficient multi-scale and shape constrained localized region-based active contour model, called the MSLCV model, has been proposed to perform semi-automatic segmentation of uterine fibroid in ultrasound images for HIFU therapy. By incorporating a new shape constraint into the localized region-based active contour, we have obtained a more precise segmentation result, avoiding the problems of boundary leakage and excessive contraction due to the low SNR, weak boundaries and intensity inhomogeneity of HIFU ultrasound images. Further, to overcome the shortcomings of the large computation time and the time-consuming nature of the segmentation process in the localized region-based active contour model, we have proposed a multi-scale algorithm that greatly improves the segmentation efficiency. Meanwhile, to solve the problem of the selection of localizing radius and initialization sensitivity, we have discussed and analysed the adaptive selection of the localizing radius and the formation of a zero narrow band. Compared with other well-known methods, the MSLCV model provides more accurate and efficient segmentation results that are closer to the manual segmentation results obtained by a specialist. In future work, we will further improve the segmentation efficiency by GPU acceleration and study the adaptive change of the shape constraint’s effect according to the quality of the HIFU ultrasound images of uterine fibroids to acquire better segmentation results.

References


