International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 11 (2015) pp. 28645-28655

http://www.ripublication.com

A Fast and Robust Level Set Method For Medical Image Segmentation

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Abstract

In this paper, we propose a fast and robust level set method for medical image segmentation. The performance of the level set based segmentation depends on the appropriate initialization of control parameters. In this paper, we estimated the controlling parameter of level set from the result of Robust Spatial Kernel FCM (RSKFCM). RSKFCM is based on standard FCM algorithm, which incorporates spatial information and uses Gaussian RBF kernel function as distance metric. We conducted experiments on medical images from different modalities. The experimental result emphasizes the effectiveness of the proposed method.

Keywords: Level set Methods, Robust Spatial Fuzzy C-Means (RSKFCM), Gaussian RBF, Medical Image segmentation.

Introduction

Medical imaging is the technique to create the internal images of the human body for clinical or medical purpose. Medical imaging has experienced tremendous progress during the past decade. Continuous innovations have been fueled by the need to improve diagnostic yield and achieve fast turnaround through robust information management, which should ultimately improve patient outcome. Primary objective of digital image processing is extracting useful information from images without human assistance. The rapid changes in digital technology tend to revolve around key modalities such as radiography, computed tomography, scintigraphy, magnetic resonance imaging and ultrasound.

Segmentation is a very important step in medical imaging. Segmentation is a process of subdividing an image into its constituent's parts or objects in the image i.e. set of pixels, pixels in a region are similar according to some homogeneity criteria such as color, intensity or texture so as to locate and identify boundaries in an image. Segmentation is an important step for medical data analysis that can help in visualization, automatic feature detection. Segmentation has the following application in medical image processing: Locate tumors and other pathologies, Measure tissue volumes, Computer guided surgery, Diagnosis, Treatment planning, Study of anatomical structures. In Literature, many researchers proposed segmentation methods. Traditional segmentation methods can be classified into three categories: Threshold based, Region based and Edge based techniques (Otsu,1975; Canny, 1986; Adams and Bischof, 1994; Beveridge et al., 1989). However, segmentation of medical images using these techniques is difficult due to poor contrast, presence of noise and limited spatial resolution. Many researchers applied the clustering technique for segmentation problem.

Many researchers (Dawant et al., 1993, Ludeke et al., 1985, Pham et al., 1997,Xu et al., 1997) used the traditional FCM to segment the medical imaging. Pham and Prince.,(1999) proposed a novel algorithm to segment the MRI images in the presence of intensity homogeneities by using Fuzzy C means. The algorithm is formulated by modifying the objective function of traditional FCM to include a multiplier field, which allows the center for each cluster to vary across the image. Chuang et al.,(2006) proposed an new MRI segmentation method based on the Spatial FCM. In proposed method the spatial constrains is incorporated into standard FCM technique. Zhou et al., (2008) proposed a mean shift based fuzzy c mean method for medical image segmentation. The proposed method incorporates the mean filed term within the standard FCMs objective function. Since mean shift can quickly and reliably finds the cluster centers, the proposed method is capable of optimally segmenting cluster within an image. Zanaty et al., (2009) proposed a new Kernalized FCM (KFCM) method for medical image segmentation. The proposed method considers the spatial constrains. The algorithm incorporates spatial information into the membership function and the validity procedure for clustering. This method automatically clusters the given image by considering the intra-cluster distance measure. Zeng et al.,(2014) proposed unsupervised method for brain tissue segmentation in MR images. This method combines an improved bias correction fuzzy c means (BCFCM) and class-adaptive Hidden Markov Random Filed modeling (HMRF). The improved BCFCM segmentation result is used as the initial labeling for class-adaptive HMRF, which is utilized to refine the segmentation results.

Level set methods have shown tremendous results for medical image segmentation. Level set method is a part of the active contour family. In literature, many researchers applied level set methods to solve medical image segmentation problem Paragios.(2003), Mitchell, (2008), Suri, (2001). However, the result of the level set method depends on the initialization of controlling parameters. Li et al., (2009) developed a liver segmentation method based on level set. In this method FCM results are used to initialize the controlling parameter of the level set. The main drawbacks of traditional FCM (1) use of Euclidean distance (2) not using spatial information. To overcome this problem (Aruna Kumar and Harish., (2014), Arun et al., (2015))proposed a Robust Spatial Kernel FCM (RSKFCM) method. RSKFCM is based on clustering algorithm, which uses spatial information and kernel distance metric. Inspired by the good performance of the RSKFCM method, in this paper, we proposed a new level set method. The controlling parameters are initialized using the robust spatial kernel FCM algorithm (RSKFCM).

The rest of the paper is organized as follows: section 2 presents background information on level set and RSKFCM algorithm. Section 3 presents proposed method. Experimental results are discussed in section 4. Section 5 concludes the paper.

Background

Robust Spatial Kernel FCM (RSKFCM)

In image processing clustering and segmentation are very close terms. In cluster techniques separates the pixels having the same characteristics. In segmentation process the result of clustering is mapped to spatial domain by physically separated regions. In Clustering the data is divided into clusters based on some similarity measures like distance, connectivity, intensity. Fuzzy c-means is well known clustering method where data points are clustered based on membership function assigned to each of them. The traditional FCM algorithm does not utilize the spatial information and this algorithm is not suitable for reveal non Euclidean structure. To overcome this problem Aruna Kumar and Harish., (2014) proposed a RSKFCM algorithm. RSKFCM algorithm incorporates spatial information into traditional FCM algorithm and replaces Euclidean distance metric with kernel distance metric.

The individual stages of Robust Spatial Kernel Fuzzy c-Means (RSKFCM) algorithm are as follows:

1. Distributes the pixel of the input image into data set X and initialize the value of centers, ε, m.
2. Compute all membership values u_{ij} of each pixel against centers such as

$$u_{ij} = \frac{\left(1-K\left(x_j, v_i\right)\right)^{-1/(m-1)}}{\sum_{k=1}^{c}\left(1-K\left(x_j, v_k\right)\right)^{-1/(m-1)}} \tag{3}$$

3. Compute the new membership value w_{ij}

$$w_{ij} = \frac{u_{ij}{}^{p} s_{ij}{}^{q}}{\sum_{k=1}^{c} u_{kj}{}^{p} s_{kj}{}^{q}} \tag{4}$$

$$s_{ij} = \sum_{k \in NK(x_j)} u_{ik}$$

Where $NK(x_j)$ represents a square window centered on pixel x_j in the spatial domain

4. Calculate the objective function J as follows:

$$J = 2\sum_{i=1}^{c}\sum_{j=1}^{N} w_{ij}^{\ m}\left(1 - K\left(x_j, v_i\right)\right) \tag{5}$$

5. Calculate new center values v_i

$$v_i = \frac{\sum_{j=1}^{n} w_{ij}^{\ m} x_j}{\sum_{j=1}^{n} w_{ij}^{\ m}} \tag{6}$$

6. Evaluate the threshold of termination condition $\left\{J(i) - J(i-1)\right\} < \varepsilon,$ where ε is a termination criterion. Stop if it is satisfied otherwise go to step 2

Level Set Segmentation

The Level set method is a numerical technique for tracking shapes and interfaces. Level set uses implicit representation of active contour to handle automatic topological changes in shapes. In segmentation, level set represents a closed curve as zero level set $\psi(t)$

$$\begin{cases} \phi(t,x,y) < 0 & (x,y)\ \textit{is inside}\ \psi(t) \\ \phi(t,x,y) = 0 & (x,y)\ \textit{is at}\ \psi(t) \\ \phi(t,x,y) > 0 & (x,y)\ \textit{is outside}\ \psi(t) \end{cases}$$

Where $\phi(t,x,y)$ is time dependent PDE function. The evolution of ϕ is determined by the numerical level set equation

$$\begin{cases} \dfrac{\partial \phi}{\partial t} + F\left|\nabla \phi\right| = 0 \\ \phi\left(0,x,y\right) = \phi_0\left(x,y\right) \end{cases}$$

Where $\left|\nabla \phi\right|$ denotes gradient, $\phi_0\left(x,y\right)$ is initial contour and F represents the comprehensive forces.

In order to stop level set evolution near optimal solution, the force F is regularized using an edge indication function g defined as follows:

$$g = \frac{1}{1 + \left|\nabla\left(G_\sigma * I\right)\right|^2}$$

Where $G_\sigma * I$ denotes convolution of the image I with G_σ Gaussian kernel.

The biggest challenge in level set segmentation is intensive computation. To overcome this problem developed a fast level set formulation

$$\frac{\partial \phi}{\partial t} = \mu \varsigma(\phi) + \zeta(g,\phi)$$

Where $\varsigma(\phi)$ denotes penalty momentum of ϕ. $\zeta(g,\phi)$ term incorporates an image gradient information by

$$\zeta(g,\phi) = \lambda \delta(\phi) div\left(g \frac{\nabla \phi}{|\nabla \phi|}\right) + vg\delta(\phi)$$

Where $\delta(\phi)$ represents Dirac function. The constants $\phi_0(x,y) = \begin{cases} -C & if\ \phi_0(x,y) < 0 \\ C & otherwise \end{cases}$ and v control the individual contributions of these terms. The initial contour $\phi_0(x,y)$ is calculated as

$$\phi_0(x,y) = \begin{cases} -C & if\ \phi_0(x,y) < 0 \\ C & otherwise \end{cases}$$

Where, C is a customable constant.

Proposed Method

Level set shows effective results for medical image segmentation. However, the accuracy of the system depends on controlling parameters setting. As discussed in previous section, there are several controlling parameters associated with level set. Table-1 presents these controlling parameters. The proposed method begins with RSKFCM clustering, whose results are utilized to initiate level set segmentation controlling parameters.

Suppose the object of interest in an RSKFCM result is $B_m : \{b_m = w_{nm},\ n = x * N_y + y\}$. It is convenient to initiate the level set function as,

$$\phi_0(x,y) = -4\varepsilon(0.5 - B_m)$$

Where ε is a constant regulating the Dirac function and B_m is a binary image obtained using threshold value.

In proposed method the result of RSKFCM used to initialize the initial contour and controlling parameters of level set. Given initial level set function ϕ_0 from RSKFCM as in equation, it is convenient to estimate the length l and area γ by

$$l = \int_I \delta(\phi_0)\, dx\, dy$$

$$\gamma = \int_I H(\phi_0)\, dx\, dy$$

Where the Heaviside function $H(\phi_0)$ is

$$H(\phi_0)=\begin{cases}1 & if \quad \phi_0 \geq 0 \\ 0 & otherwise\end{cases}$$

We observe that, when the object of interest is large, the level set will evolve faster. In this case the ratio $r = \delta/l$ will also be large. Therefore it is reasonable to assign the time step as r in the proposed method. The penalty coefficient μ is calculated as $\mu = 0.2/r$. The comparative conservation λ is calculated as $\lambda = 0.1r$

The artificial balloon force is calculated using the membership value of RSKFCM algorithm. In proposed method the membership of each pixel w_k is defined as distance to specific object of interest B_m. The balloon force $G(B_m)$ is calculated as

$$G(B_m)=1-2B_m$$

Table 1: Controlling Parameters of Level Set

Parameter	Significance
σ	Controlling the spread of Gaussian smoothing function
C	Controlling the gradient strength of initial level set function
ε	Regulator of Dirac function
μ	Weighting coefficient of penalty term
λ	Coefficient of the contour length for smoothness regulation
v	Artificial balloon force

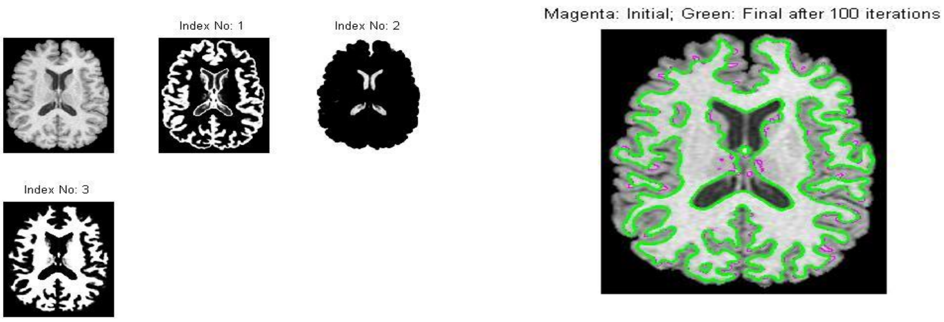
Experimental Results

This section evaluates the performance of the proposed method. In this paper, to test the efficiency of the proposed method we conducted extensive experiments on medical images from different modalities, including MRI brain images, CT scan of Lung images, MRI Breast images and MRI Cervical Cytology images. We implemented the proposed method with matlab R2013b.

MRI brain images are downloaded from the Brainweb. The brain has four components white matter (WM), gray matter (GM), Cerebrospinal fluid (CSF), Background. The first experiment was designed to evaluate the normal brain segmentation. Figure 1(a) shows the segmentation result of normal brain image using RSKFCM algorithm. Figure 1(b) shows the final segmentation result of Cerebrospinal fluid using proposed method. Figure 2 (a) shows the segmentation result of brain images with tumor using RSKFCM method. Figure 2(b) shows the final segmentation of tumor cells using proposed method.

The second sets of images considered for experimentation are Lung images. We collected 50 different CT scan lung images from hospital. From expert opinion the Lung images have three components: Lungs, Vessels, Junction. Figure 3 (a) shows initial segmentation result using RSKFCM algorithm. Figure 3 (b) shows final segmentation results using proposed method.

For experimentation, we considered 50 MRI breast images. The breast images have three components: Normal, tumor, background. Figure 4 (a) shows the initial segmentation results using RSKFCM algorithm. Figure 4 (b) shows the final segmentation result using proposed method.

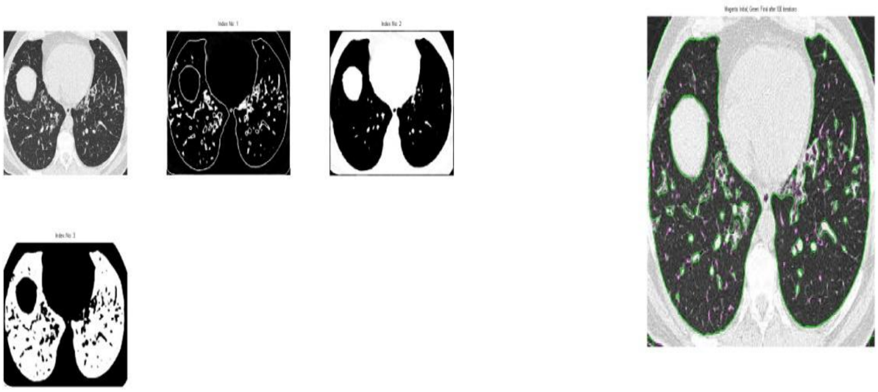


(a) (b)

Figure 1: Level set segmentation of MRI brain normal image: (a) Initial segmentation of MRI brain image using RSKFCM (b) Final segmentation of cerebral tissues using proposed level set method.

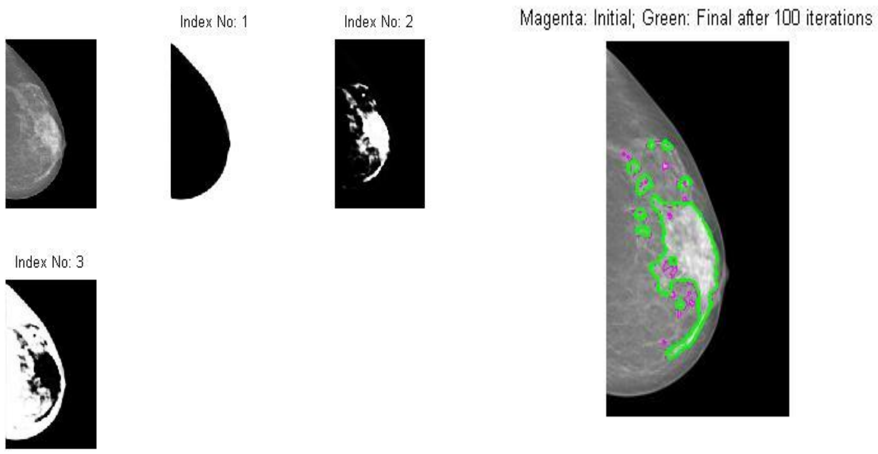
(a) (b)

Figure 2: Level set segmentation of MRI brain tumor image: (a) Initial segmentation of MRI brain image using RSKFCM (b) Final segmentation of tumor using proposed level set method.



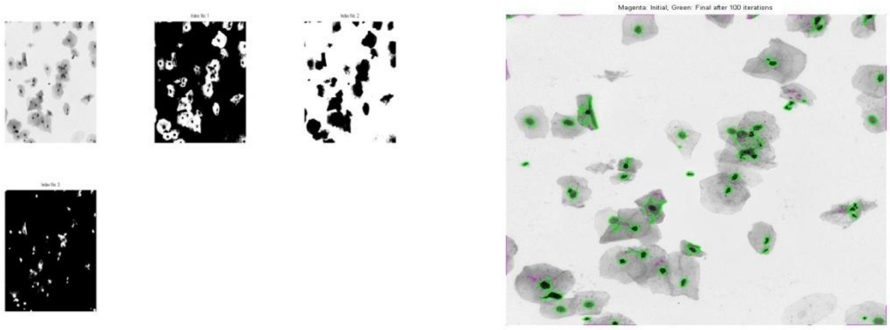
(a) (b)

Figure 3: Level set segmentation of CT scan Lung image: (a) Initial segmentation of Lung image using RSKFCM (b) Final segmentation of Lung tumor using proposed level set method.



(a) (b)

Figure 4: Level set segmentation of MRI breast image: (a) Initial segmentation of MRI breast image using RSKFCM (b) Final segmentation of breast tumor using proposed level set method.



(a) (b)

Figure 5: Level set segmentation of Cervical Cytology image: (a) Initial segmentation of Cervical Cytology image using RSKFCM (b) Final segmentation of Cervical Cytology image nuclei using proposed level set method.

The fourth sets of images considered for experimentation are Cervical Cytology images from Pap smear. The Pap smear is a screening test used to detect pre-cancerous and cancerous processes, which consists of a sample of cells collected from the cervix that are smeared onto a glass slide and further examined under a microscope. Figure 5 (a) shows segmentation results using RSKFCM algorithm. Figure 5(b) shows the localization of nucleus using proposed method.

In summary, the proposed method gives a good segmentation results on medical images. Fuzzy clustering algorithm is able to adaptively obtain the approximate boundaries of potential components of interest. Since, RSKFCM incorporate spatial information and uses kernel metric, it shows less susceptible to different types of noise. Hence it is suitable to initiate level set evolution for medical image segmentation.

Conclusion

Level set method is a part of the active contour family and has been broadly applied for medical image segmentation. The result of level set depends on the initialization of controlling parameter. In this paper, we have proposed new level set method for automated medical image segmentation. The proposed method utilizes RSKFCM algorithm to initialize the controlling parameters. The RSKFCM algorithm can approximate the boundaries of interest well. Therefore, levels set evolution will start from a region close to genuine boundaries. Performance evaluation has been carried out on different types of medical images. The results were confirmed promising.

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