Medical image segmentation using optimum thresholded Reaction-diffusion active contour model

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Abstract

Background: The diagnosis of diseases like Attention Deficit Hyperactive Disorder and cervical cancer needs an efficient segmentation technique to identify the regions of problematic areas with low cost and CPU time.

Method:

The Proposed RD – ACM methodused to identify the ADHD and cervical cancer affected areas. In this method, the acquired input images are enhanced, converted into binary images using optimal threshold value andthe connected components are extracted using label matrix. The initial contours are generated and taken as the zero level set.Neumann Boundary is generated to specify the size of the image where the Level Set Evolution (LSE) process will take place. Then the image is smoothen by Heaviside and Dirac delta function. The proposed method provides a piecewise constant solution is derived by the introduction of diffusion term into LSE.A Two-step splitting method iteratively solves the RD-LSE equation is introduced to first iterate the LSE equation, and then solve the diffusion equation and to regularize the level set function obtained in the first step. The process is repeated until the final contours of the objects are extracted.

Results: Significant promising segmentation results are noticed for all type of images with boundary antileakage. It can be applied to solve both variational as well as partial differential equation based level set methods. The application of Reaction- Diffusion term ensures stability, and thus the complex and costly reinitialization procedure is completely eliminated from LSE.

Conclusion: Anovel medical image segmentation technique using optimal threshold Reaction-Diffusion Active Contour model (RD – ACM) is found to be more promising technique in the diagnosis of ADHD.

***Keywords**:* Reaction, Diffusion, Active contour, Level Set Evolution, Neumann Boundary.

I. Introduction

Medical images with lot of noise and intensity inhomogenity can be efficiently segmented by Active Contour Models. The ACM model starts with arbitrary initial shape and iterated to move towards the object boundary [1]. During this deformation process the energy is minimized and it reaches to local minimum when the contour is spatially aligned with the desired image features. Thus the segmentation is done by the Energy Minimization Process which can be solved by Parametric ACM [2][3]. But the PACM has some drawbacks in handling the topological changes and the dependency of parameterization [4].The Level Set Method (LSM) later proposed by Osher and Sethian implicitly represents the curve by the zero level of a high dimensional function, and it significantly improves ACM by being free of these drawbacks [5].

The Level Set Evaluation (LSE) of partial differential equation (PDE) based LSM is directly derived from the geometric consideration of the motion equations, which can be used to implement most of the parametric ACMs. The LSE of variational LSM is derived via minimizing a certain energy functional defined on the level set [6].Moreover, the variational LSM can be easily converted into PDE-based LSM by changing slightly the LSE equation while keeping the final steady state solution unchanged [7].

In traditional LSMs, to keep numerical stability the Level Set Function (LSF) is initialized to be a Signed Distance Function (SDF). Since the LSF often becomes very flat or steep near the zero level set in the LSE process a time consuming re-initialization procedure is applied periodically to enforce the degraded LSF being an SDF. Chopp et.al, proposed a more efficient method by restricting the front movement and the re-initialization within a band of points near the zero level set which is very difficult to locate and discretize the interface. In order to make the interface stationary during re-initialization, the two-phase incompressible flow method was proposed. Some other methods use a true upwind discretization near the interface to make the interface localization accurate, and it can keep the interface stationary [8]. All the above mentioned re-initialization methods, have the risk of preventing new zero contours from emerging, which may cause undesirable results for image segmentation, such as failures in detecting the interior boundary.The variational LSMs without re-initialization may have higher efficiency and easier implementation over the traditional methods [9].

In this paper, a new LSM, namely the Optimum Thresholded Reaction-Diffusion (RD) method, which is completely free from the costly time consuming re-initialization procedure, is proposed. The paper is organized as follows. Section II describes Level Set Methods. Section III discusses the proposed RD-ACM. Experimental results and analysis are providedin Section IV and Section V concludes the paper.

2. Level set methods

Moving interfaces can be easily tracked by a numerical technique called Level Set Method (LSM). It evolves a contour (in two dimensions) or a surface (in three dimensions) implicitly, defined as a higher dimensional function, called the level set function ϕ(x, t). In level set formulation of moving fronts denoted by C, are represented by the zero level setC(t)={(x, y)|ϕ(t, x, y)= 0} of a level set function ϕ(t, x, y)[10]. The evolution equation of the level set function ϕ can be written in the following general form:

$$\frac{\partial \phi}{\partial t} + F|\nabla \phi| = 0 \qquad (1)$$

which is called level set equation. The function *F* is called the speed function. For image segmentation, the function F depends on the image data and the level set function ϕ. The advantage of using this method is that topological changes such as merging and splitting of the contour or surface are catered implicitly.

For a general curve C, φ can be defined as a signed distance function to C[11].

$$\begin{cases} \phi(x,t) = 0 & x \in C \\ \phi(x,t) < 0 & x \in \text{inside}C \\ \phi(x,t) > 0 & x \in \text{outside}C \end{cases} \qquad (2)$$

The image is divided into three regions based on the value ofφ, inside the level set ($\varphi< 0$), boundary ($\varphi =0$) and outside the level set ($\varphi>0$). Then, an iterative procedure is applied, which uses an edge stopping function to decide the rate at which, the curve evolves. The evolution of curve happens in a direction normal to itself and the evolution stops when the curve meets an object or boundary. Curve evolution *C(t)* is performed over the time *t*, where $t \geq 0$. The positive sign indicates that the point lies inside the curve and the negative sign indicates that the point is outside the closed curve. When the curve evolves in time; the value of the function at each grid point also evolves. The level set method updates the value of the function at each point over small increments of time.

3. Medical image segmentation using optimum thresholded Reaction-diffusion active contour model

The proposed segmentation algorithm is a novel technique that can be applied on medical images to separate the regions or objects. The cervical cytology and brain images are taken as input images which are thresholded and the connected components are identified. The label matrix is created with different values for different connected components and the corresponding initial contour curves are generated. The curve moves under the influence of a speed law which depends on different factors that means different features of the image. LSF with zero level set is used to represent the object contour. During evolution, the LSF may become too flat or too steep near the zero level set, causing serious numerical errors which can be rectified by employing reinitialization procedure periodically to reshape it to be an SDF and make the LSE stable. Hence Reinitialization is a costly time consuming process. The RD equation is constructed with a diffusion term and applied into the conventional LSE equation. The diffusion term "*εΔφ*" is approximated as:

$$\emptyset_t = \varepsilon\Delta\emptyset - \frac{1}{\varepsilon} L(\emptyset) \qquad (3)$$

where ε is a small positive constant, *L(φ) = −F|Δφ|* for LSM or *L(φ) = −Fδ* (ϕ) for variational LSE. The LSE has two dynamic processes: the Diffusion term "*εΔφ*" gradually regularizes the LSF to be piecewise constant in each segment domain, and the Reaction term "$-\varepsilon^{-1}L(\varphi)$" forces the final stable solution to *L (φ) = 0*. The above mentioned level set equation has the intrinsic problem of the stiff parameter ε^{-1} and makes difficult to implement. In this paper, a two step splitting method is proposed to implement Eq. (3) to reduce the side effect of the stiff parameter ε^{-1}. The entire process is repeated and the final level set is obtained which is the contour of the image components

A. Preprocessing

The acquired input images are enhanced and converted into binary images using optimal threshold value. The connected components are identified by block &white connected components method and label matrix is created with the integer values greater than or equal to 0. The background pixels are labeled as 0 and the pixels of object 1 is labeled as 1, object 2 as 2 and so on. To visualize the labeled regions, the label matrix is converted into an RGB color image.

B. Initial Contour Generation

The simplest form of a level set representation is a Rectangle. The *Greatest Distance Value (C)* is calculated from the preprocessed image. Then, the image will have only two values ie., the value of the pixel inside of the initial contour has *Negative Distance Value (-C)* and the value of the pixel outside of the initial contour has *Positive Distance Value (C)*. The intermediate pixel between the inside and outside of the initial contour has the value 0. The Greatest Distance Value is approximated as

$$\textit{Greatest distance} = \sqrt{a^2 + b^2} \qquad (4)$$

where *a* denotes the number of rows and *b* denotes the number of columns in an input image. Then the Level set evolution is started according to the speed value *F.*

C. *Level Set Evolution*

The Level Set Evolution Process is applied on the preprocessed image. In this, first *Neumann Boundary Condition* is defined. This function provides the boundary for an image. An image is considered as number of rows and number of columns. Let the rows and columns be *M*, *N* respectively. When applying the Neumann Boundary Condition, the size of the image is reduced by 2 or 3 rows and columns from the original size. Actually, this process will reduce the size of the image only to some least value.It will not affect the original size of the image .Within this specific boundary, the Level Set Evolution process will take place. Then image smoothen process is applied using Heaviside and Dirac delta.

The Heaviside function usually denoted by H, is a discontinuous function whose value is zero for negative argument and one for positive argument. Since H is mostly used as a distribution, *H (φ)* takes 0 for *φ < 0* and 1 otherwise for image smoothening. The Heaviside function is approximated by:

$$H_\varepsilon(x) = \frac{1}{2} + \frac{1}{\pi}\arctan\frac{x}{\varepsilon} \qquad (5)$$

The *Dirac delta function δ* acts on all level curves, and new contours can appear spontaneously, which makes it tend to yield a global minimum. The Dirac function is approximated by:

$$\delta_\varepsilon(x) = \frac{1}{\pi}\frac{\varepsilon}{x^2+\varepsilon^2} \quad (6)$$

After the image smoothen process, the Speed Function is calculated. According to *Speed Function or Law F*, the initial curve is moved towards the edges of the input image, that is, the LSF is evoluted using *TSSM*. The speed law F is approximated by

$$F = -\lambda_1\left(Img - C_1(\emptyset)\right)^2\lambda_2 + \left(Img - C_2(\emptyset)\right)^2 \quad (7)$$

where $\lambda 1$, $\lambda 2 > 0$are fixed parameters, C_1 *(φ)* and C_2 *(φ)* are the average intensity value of the pixels inside and outside of the Zero Level Set, respectively. C_1 *(φ)* and C_2 *(φ)* are approximated by

$$C_1 = \frac{\int_\Omega I\left(1-H_\varepsilon(\emptyset)\right)dx}{\int_\Omega \left(1-H_\varepsilon(\emptyset)\right)dx} \quad (8)$$

$$C_2 = \frac{\int_\Omega I\left(H_\varepsilon(\emptyset)\right)dx}{\int_\Omega \left(H_\varepsilon(\emptyset)\right)dx} \quad (9)$$

Two-Step Splitting Method (TSSM)

A TSSM algorithm to implement RD has been proposed in [8]. In our proposed work, the diffusion function is used to generate curvature-dependent motion; the LSE is driven by the reaction function, i.e., the LSE equation. Therefore, it is proposed to use the diffusion function to regularize the LSF generated by the reaction function. To this end, the following TSSM is proposed to solve the RD.

Step 1: Solve the reaction term $\varphi_t = -\varepsilon^{-1}L(\varphi)$ with some time t_1 to obtain the intermediate solution.

Step 2: Solve the diffusion term $\varphi_t = \varepsilon\Delta\varphi$ with sometime t_2, and then the final level set is set.

The diffusion process in Step 2 can make the LSF smooth while reducing to some extent the numerical error generated in Step 1, we can easily choose a proper $\Delta t1$, $\Delta t2$ to make the evolution stable. Finally, the process is repeated until the final contours of the objects are extracted.

ALGORITHM

The procedure for the proposed Optimum Thresholded Reaction - Diffusion Level Set Model is given below,

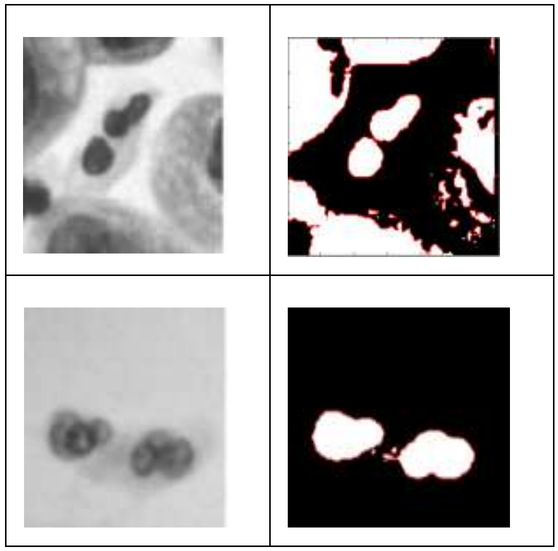
1) Read an input Image.
2) Apply preprocessing.
3) Create Initial Contour.
4) Find the Greatest Distance value C.
5) Define Neumann Boundary Condition.
6) Smoothen the image using Heaviside & Dirac Function
7) Calculate Speed Function using the average intensity value of the pixels inside and outside of the Zero Level Set.
8) Compute $\phi = \phi - \Delta t_1 * L(\phi)$.
9) Compute $\phi = \phi + \Delta t_2 * \Delta(\phi)$.
10) Generate the contours. Repeat steps 6 to 10 until the objects are segmented.

IV. Experimental results

The performance of the proposed technique has been tested with various images especially cervical cytology, brain and synthetic images and the results are shown in Fig 1,2&3. The proposed **RD – ACM** method shows very good segmentation results for the images with weak edges merge and split types of images without any boundary leakage.

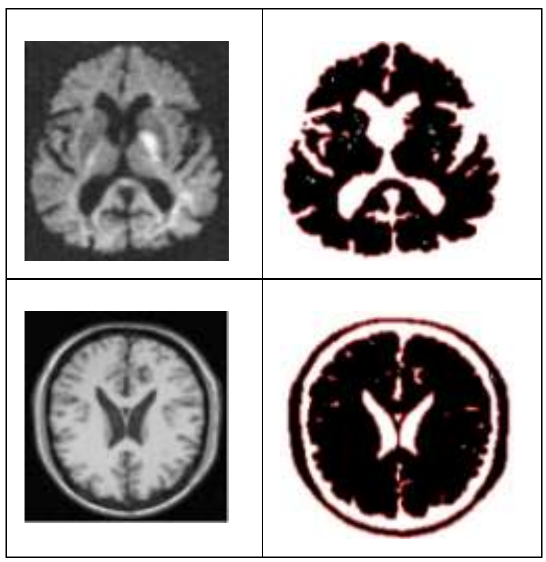
The performance of the method is evaluated by the Number of Iterations and the CPU Time taken. Table.1 lists the performance evaluation of the proposed method on various cervical, brain and synthetic images.

*Figure 1. (a) Cervical images (b) Proposed **RD – ACM** output*



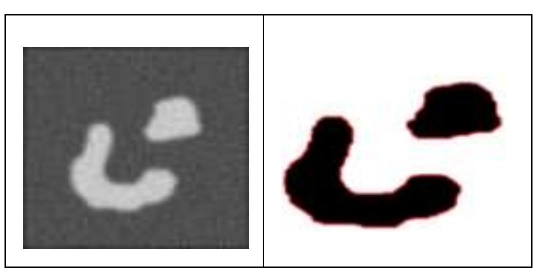
(a) (b)

*Figure 2. (a) Brain images (b) Proposed **RD – ACM** output*



(a) (b)

*Figure 3. (a) Synthetic image (b) Proposed **RD – ACM** output*



(a) (b)

Table 1. Performance evolution

Images	Attributes	
	No. of Iterations	*CPU Time(Seconds)*
1	300	15.158
2	280	7.162
3	150	3.761
4	300	9.865
5	750	25.259

Graphical representation of Performance Evolution of the proposed RD – ACM method for No of Iterationsand CPU time is shown in Fig 4&5. It has been identified that the synthetic images take more CPU time for processing and number of iterations required for generating the final contour is also more when compared to medical images. Among the medical images the proposed **RD – ACM**gives better results for brain images when compared to cervical cytology images. So it has been found that **RD – ACM**method can play a vital role in segmenting the regions of the brain images into grey and white matter for the analysis of Attention Deficit Hyperactivity Disorder problem which is our future research work.

Figure 4. Graphical representation of Performance Evolution of RD – ACM method for No of Iterations

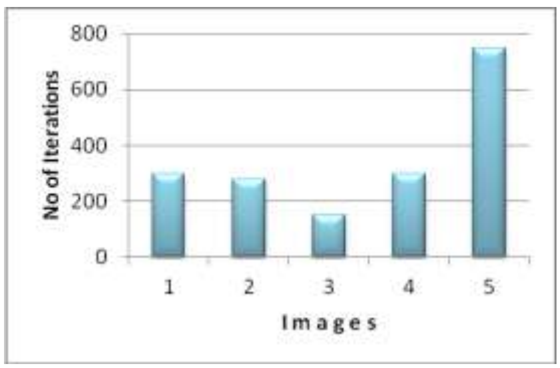
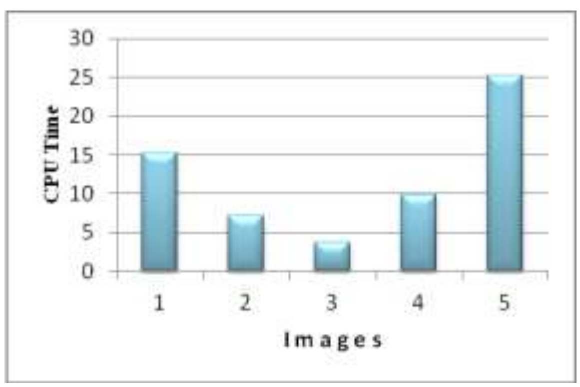


Figure 5. Graphical representation of Performance Evolution of RD – ACM method for CPU Time.



4. Conclusion

Optimum Thresholded reaction-diffusion based level set evolution (LSE) has been proposed, which is completely free of the re-initialization procedure required by traditional level set methods. A TSSM was then proposed to effectively solve the RD based LSE. The proposed RD method can be generally applied to either variational level set methods or PDE-based level set methods. It can be implemented by using the simple finite difference scheme. The RD method has the following advantages over the traditional level set method and state-of-the-art algorithms: It can be applied to the PDE-based level set methods and variational ones and better performance on weak boundary anti-leakage, the implementation of the RD equation is very simple and it does not need the upwind scheme at all. It is also robust to noise. The experiments on medical (cervical & brain) images demonstrated the promising performance of the proposed approach.

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