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Distance regularization Level Set Evolution for Blood Cell Image Segmentation

Prof.Dipali N.Dhake[1], Rupali Kawade[2], Triveni Dhamale[3]
[1](E&TC, PCCOE&R/SPPU, India)
2(E&TC, PCCOE&R/SPPU, India)
3(E&TC, PCCOE&R/SPPU, India)

Abstract: *Image segmentation has been used to locate the boundaries and objects in images. Medical image segmentation is important part of clinical diagnostic tool. The process of accurate segmentation of medical images is very important and crucial task by clinical tools.Here Distance regularization Level Set Evolution algorithm is used for segmentation of Blood cell images. Proposed method eliminates the need for reinitialization and thereby avoids its induced numerical error. In this paper first use canny operator for edge detection, then use Distance Regularization Level Set Evolution algorithm for segmentation. The distance regularization term is defined with a potential function such that the derived level set evolution has a unique forward-and-backward (FAB) diffusion effect, which is able to maintain a desired shape of the level set function, particularly a signed distance profile near the zero level set.*

I. Introduction

Segmentation is useful to simplify or change representation of image into something that is more meaningful. Image segmentation has been used to locate the boundaries and objects in images. Edge detection is very important for image segmentation. It reduces amount of data and filter out useless information, while preserving the important structural properties of images. The canny edge detector has a simple approximate implementation in which edges are marked at maxima in gradient magnitude of a Gaussian-smoothed image. The performance of the canny algorithm depends heavily on the adjustable parameters 'σ' which is the standard deviation for the Gaussian filter, and the threshold values, 'T1' and 'T2'. Canny operator overcomes the disadvantages of tradition edge detection operators, such as Roberts operator, Sobel operator, Prewitt operator. It can detect almost all edges, and is one of the best edge detection algorithms. So, considering the different medical images database, a canny operator based distance regularization level set evolution (DRLSE) algorithm. The algorithm combines the advantages of canny operator which can orient the boundary accurately and the idea that DRLSE algorithm continuously evolves the boundary in image space. Proposed algorithm used for database of Blood cell medical images.

II. Material And Methods

A. Canny Edge Detection Algorithm

The canny edge detection operator was developed by John F.Canny in 1986 and uses a multi-stage algorithm to detect a wide range of edges in images. Most importantly, canny also produced a computational theory of edge detection explaining why the technique works. canny's aim was to discover the optimal edge detection algorithm. In this situation, an "optimal" edge detector means:

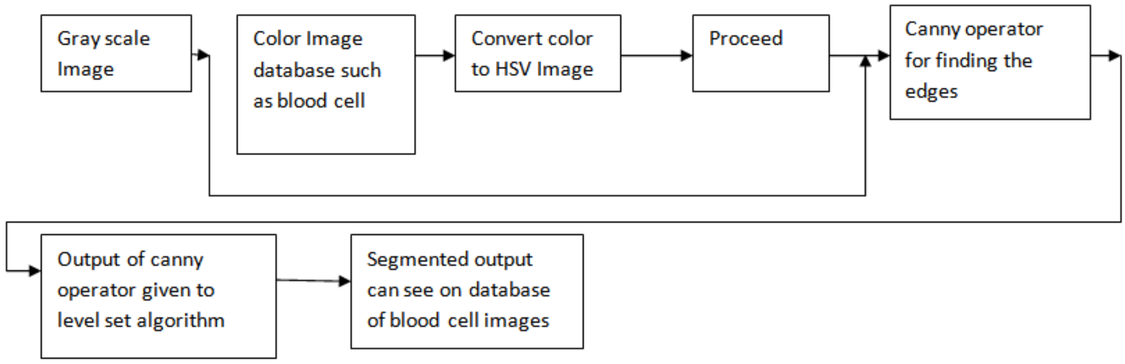
1. Detection:- It is important that edges occurring in imagesshould not be missed and that there be no responses to non-edges.
2. Localization:-The distance between the edge pixels asfound by the detector and the actual edge is to be at a minimum.
3. Number of responses:-A third criterion is to have only oneresponse to a single edge.

Canny edge detection algorithm is computationally more expensive compared to Sobel, Prewitt and Robert's operator.

The algorithm runs in 5 separate steps**:**

1. Smoothing: Blurring of the image to remove noise.
2. Finding gradients: The edges should be marked where thegradients of the image has large magnitudes.
3. Non-maximum suppression: Only local maxima should bemarked as edges.
4. Double thresholding: Potential edges are determined bythresholding.
5. Edge tracking by hysteresis: Final edges are determined bysuppressing all edges that are not connected to a very certain strong) edge.

Design:-



B. DRLSE

In level set methods, a contour of interest is embedded as the zero level set of an LSF. Although the final result of a level set method is the zero level set of the LSF, it is necessary to maintain the LSF in a good condition, so that the level set evolution is stable and the numerical computation is accurate. This requires that the LSF is smooth and not too steep or too flat (at least in a vicinity of its zero level set) during the level set evolution. This condition is well satisfied by signed distance functions for their unique property $|\nabla\varnothing|=1$, which is referred to as the signed distance property. For the 2-D case as an example, we consider a signed distance function z=$\varnothing$ (x,y)as a surface. Then, its tangent plane makes an equal angle of 45 with both the -plane and the -axis, which can be easily verified by the signed distance property $|\nabla\varnothing|=1$. For this desirable property, signed distance functions have been widely used as level set functions in level set methods. In conventional level set formulations, the LSF is typically initialized and periodically reinitialized as a signed distance function. In this section, we propose a level set formulation that has an intrinsic mechanism of maintaining this desirable property of the LSF.

a. Energy Formulation With Distance Regularization

Let $\emptyset: \Omega \rightarrow \mathcal{R}$ be a LSF defined on a domain . We define an energy functional$\mathcal{E}(\emptyset)$ by

$\mathcal{E}(\emptyset) = \mu\mathcal{R}_p(\emptyset)\mathcal{E}_{ext}(\emptyset)$……….………………………………………….(1)

where $\mathcal{R}_p(\emptyset)$ is the level set regularization term defined in the following, $\mu > 0$ is a constant, and $\mathcal{E}_{ext}(\emptyset)$ is the external energy that depends upon the data of interest (e.g., an image for image segmentation applications). The level set regularization term $\mathcal{R}_p(\emptyset)$ is defined by

$$\Re_p(\phi) \triangleq \int_\Omega p(\nabla\phi)\,dx \quad \text{………………………………………………………………….(2)}$$

Where p is a potential (or energy density) function. p: $[0,\infty) \rightarrow \mathcal{R}$The $\mathcal{E}_{ext}(\emptyset)$ energy is designed such that it achieves a minimum when the zero level set of the LSF$\emptyset$ is located at desired position.

A naive choice of the potential function is p(s) =s2 for the regularization term, which forces $|\nabla\emptyset|$to be zero. Such a level set regularization term has a strong smoothing effect, but it tends to flatten the LSF and finally make the zero level contours disappear. In fact, the purpose of imposing the level set regularization term is not only to smooth the LSF, but also to maintain the signed distance property$|\nabla\emptyset| = 1$, at least in a vicinity of the zero level set, in order to ensure accurate computation for curve evolution. This goal can be achieved by using a potential function with a minimum point s=1, such that the level set regularization term is minimized when$|\nabla\emptyset| = 1$. Therefore, the potential function should have a minimum point at s=1 (it may have other minimum points).The corresponding level set regularization term $\mathcal{R}_p(\emptyset)$ is referred to as a distance regularization term for its role of maintaining the signed distance property of the LSF. A simple and straightforward definition of the potential pfor distance regularization is

$$p = p_1(s) \triangleq \frac{1}{2}(s-1)^2 \quad \text{……….………………………………………………………………. (3)}$$

which has s=1as the unique minimum point. With this potential,$p = p_1(s)$ the level set regularization term $\mathcal{R}_p(\emptyset)$ can be explicitly expressed as

$$p(\phi) = \frac{1}{2}\int_\Omega (|\nabla\phi| - 1)^2\,dx \quad \text{……………………………………………………….……………….(4)}$$

which characterizes the deviation of from a signed distance function.

The energy functional $p(\emptyset)$ was proposed as a penalty term in [1] an attempt to maintain the signed distance property in the entire domain. However, the derived level set evolution for energy minimization has an undesirable side effect on the $LSF\emptyset$ in some circumstances. To avoid this side effect, we introduce a new potential function in the distance regularization term . This new potential function is aimed to maintain the signed distance property $|\nabla\emptyset| = 1$ only in a vicinity of the zero level set, while keeping the LSF as a constant, with$|\nabla\emptyset| = 0$, at locations far away from the zero level set. To maintain such a profile of the LSF, the potential function must have minimum points s=1& s=0 at and .Such a potential is a double-well potential as it has two minimum points (wells). Using this double-well potential $p = p_2$not only avoids the side effect that occurs in the case of$p = p_1$, but also offers some appealing theoretical and numerical properties of the level set evolution.

b. Gradient Flow for Energy Minimization

In calculus of variations a standard method to minimize energy functional$F(\emptyset)$ is to find the steady state solution of the gradient flow equation

$$\frac{\partial \phi}{\partial t} = -\frac{\partial F}{\partial \phi} \quad \text{.......} (5)$$

where$\frac{\partial F}{\partial \emptyset}$ is the Gâteaux derivative of the functional $F(\emptyset)$

The distance regularization effect in DRLSE can be seen from the gradient flow of the energy$\mu\mathcal{R}_p(\emptyset)$.

$$\frac{\partial \phi}{\partial t} = \mu\, div(d_p(|\nabla \phi|)\nabla \phi) \quad \text{.......}(6)$$

This flow can be expressed in standard form of a diffusion

$$\frac{\partial \emptyset}{\partial t} = div(D\nabla\emptyset) \quad \text{.......}(7)$$

with diffusion rate $D = \mu d_p(|\nabla\emptyset|)$. Therefore, the flows in (5) and (6) have a diffusion effect on the level set function . This diffusion is not a usual diffusion, as the diffusion rate can be positive or negative for the potential used in DRLSE. When $d_p(|\nabla\emptyset|)$is positive, the diffusion is forward diffusion, which decreases $|\nabla\emptyset|$. When $d_p(|\nabla\emptyset|)$e is negative, the diffusion is backward diffusion, which increases $|\nabla\emptyset|$. Such diffusion is called a forward-and-backward (FAB) diffusion.

c. Distance Regularization Effect

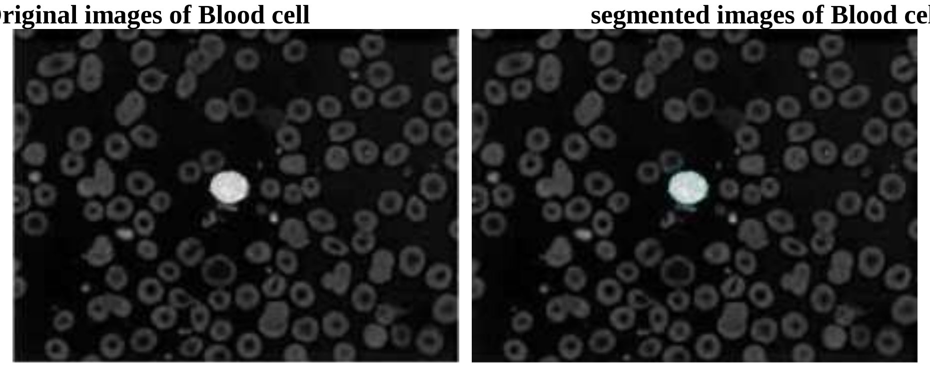
We demonstrate the distance regularization effect of DRLSE by simulating the FAB diffusion (6) with the initial function being a binary step function. The binary step function is defined by

$$\emptyset_0(x) = \begin{cases} -c_0, & if x \in R_0 \\ c_0, & otherwise \end{cases} \quad \text{.......}(8)$$

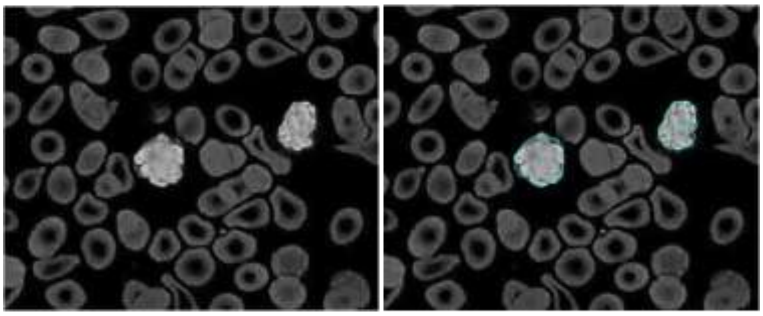
where c_0 is a constant, and R_0 is a region in the domain. Despite the irregularity of the binary step function, the FAB diffusion is able to evolve the LSF into a function with desired regularity. It is worth noting that a binary step function can be generated extremely efficiently. The effect of the distance regularization with the double-well potential can be seen from the following numerical simulation of the FAB diffusion.

III. Result

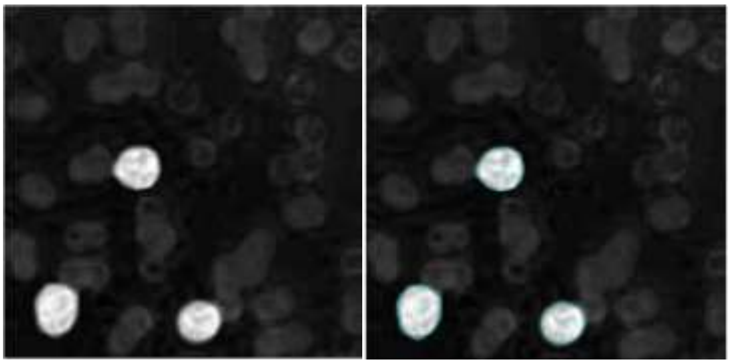
Original images of Blood cell **segmented images of Blood cell**



(a) **(b)**



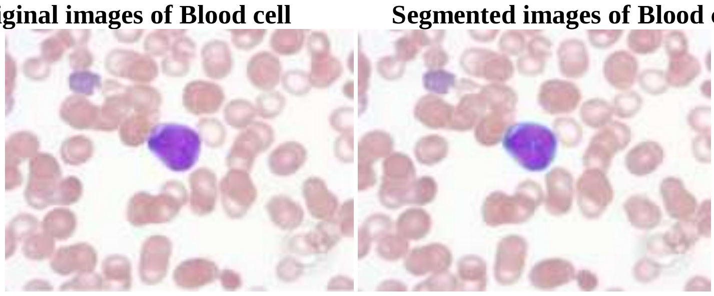
(c) (d)



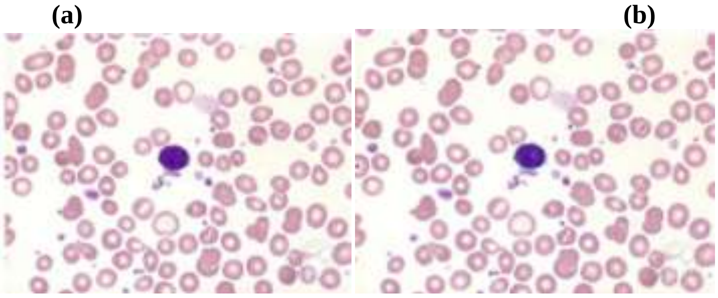
(e) (f)

Figure No.1 Segmentation of Grayscale Blood cell images by using DRLSE algorithm

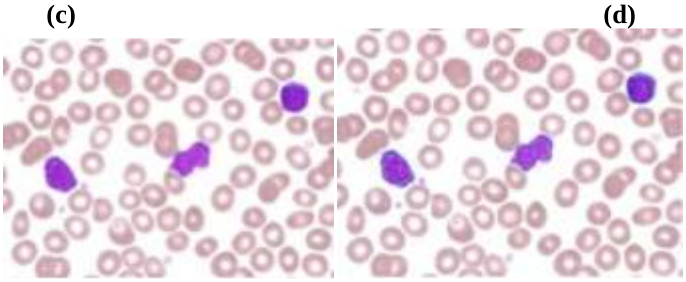
Original images of Blood cell **Segmented images of Blood cell**



(a) (b)



(c) (d)



(e) (f)

Figure No.2 Segmentation of color Blood cell images by using DRLSE algorithm

IV. Conclusion

We have presented Distance Regularization Level Set Evolution (DRLSE) for blood cell image segmentation. Proposed method eliminates the need for reinitialization and thereby avoids its induced numerical error. DRLSE in which the regularity of the level set function is intrinsically maintained during the level set evolution. The distance regularization term is defined with a potential function such that the derived level set evolution has a unique forward-and-backward (FAB) diffusion effect, which is able to maintain a desired shape of the level set function, particularly a signed distance profile near the zero level set.DRLSE algorithm is used for Color images as well as grayscale blood cell images.

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