An Optimization Technique for Medical Image Segmentation

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Abstract—This paper aims at studying the level set segmentation technique using Variational Level Set Formulation techniques without reinitialisation applied on medical images and analyzing the results obtained after applying various filters to the segmented images. The various steps taken in the development of the program and then the testing of the simulation program with various medical images are described and the test samples are obtained from set of CT images, MRI images using MATLAB simulation programs.

Keywords— Level Set Segmentation, Reinitialisation, CT, MRI images.

I. INTRODUCTION

Medical images play important role in assisting health care providers to access patients for diagnosis and treatment. Studying medical images depends mainly on the visual interpretation of the radiologists. However, this consumes time and usually subjective, depending on the experience of the radiologist. Consequently the use of computer-aided systems becomes very necessary to overcome these limitations. Artificial Intelligence methods such as digital image processing when combined with others like machine learning, fuzzy logic and pattern recognition are so valuable in Image techniques can be grouped under a general framework; Image Engineering (IE). This is comprised of three layers: image processing (lower layer), image analysis (middle layer), and image understanding (high layer), as shown in Fig 1. Image segmentation is shown to be the first step and also one of the most critical tasks of image analysis. Its objective is that of extracting information (represented by data) from an image via image segmentation, object representation, and feature measurement, as shown in Fig 1. Result of segmentation; obviously have considerable influence over the accuracy of feature measurement [2]. The computerization of medical image segmentation plays an important role in medical imaging applications. It has found wide application in different areas such as diagnosis, localization of pathology, study of anatomical structure, treatment planning, and computer-integrated surgery. However, the variability and the complexity of the anatomical structures in the human body have resulted in medical image segmentation remaining a hard problem [3].

Based on different technologies, image segmentation approaches are currently divided into following categories, based on two properties of image.

• Detecting Discontinuities
  It means to partition an image based on abrupt changes in intensity [1], this includes image segmentation algorithms like edge detection.

• Detecting Similarities
  It means to partition an image into regions that are similar according to a set of predefined criterion [1]; this includes image segmentation algorithms like Thresholding, region growing, region splitting and merging.

However, medical images are often corrupted by inherent noise and artifacts which could make it difficult to extract accurately information, and hence compromising the quality of pathological diagnosis. One of challenging issues is the intensity inhomogeneity, which can be observed as a relative variation of the intensity in the object to be detected. This effect is due to a typical artifacts known in medical images, such as magnetic resonance (MR), computed tomography (CT), and positron emission tomography (PET) images.
II. RELATED WORK

In the literature, active contour models (ACM) have gained more interest due to their performance in terms of accuracy. The first ACM has been introduced by Kass et al. [4], and many applications of the ACM for medical images have been proposed [3], [5]. The main idea consists in deforming an initial curve towards object boundaries, under some constraints.

Traditionally, the existing ACM can be classified into two main categories: the edge-based ACM and the region-based ones. To cope with the intensity inhomogeneity, many approaches were proposed to incorporate local image intensities into the energy function [6] which was minimized by using a level set function and the Euler-Lagrange equation.

III. PROPOSED METHOD

A. Level set method:

The level set method (LSM) is one of a numerical technique used for tracking interfaces and shapes. The greatest advantage of the level set method is that we can perform particular numerical computations involving curves and surfaces on a fixed Cartesian grid without having to set parameters of these objects which can be done through Eulerian approach.

Also, the level set method makes user friendly and easy to follow shapes that change topology frequently, for example when a shape splits in two, develops holes, or the reverse of these operations also.

The figure (1) illustrates important ideas about the level set method. In this upper-left corner we see a shape; that is, a bounded region with a well-behaved boundary. Below it, the red surface is the graph of a level set function \( \varphi \) determining this shape, and the flat blue region represents the \( x - y \) plane.

Therefore boundary of the shape is then the zero level set of \( \varphi \), while the shape itself is the set of points in the plane for which \( \varphi \) is positive (interior of the shape) or zero (at the boundary). In the top row we see the shape changing its topology by splitting in two. It would become difficult to describe this transformation numerically by parameterizing the boundary of the shape and following its evolution.

B. The level set equation

If the curve \( \Gamma \) moves in the normal direction with respect to speed \( \mathbf{v} \), then the level set function \( \varphi \) satisfies the level set equation as mentioned below

\[
\frac{\partial \varphi}{\partial t} = \mathbf{v} \cdot \nabla \varphi.
\]

…‥1

where \( \mathbf{v} \) is a scalar velocity (speed) function depending on the local geometric properties (e.g. curvature) and on the external parameters related to the input data (e.g. image gradient). \( \nabla \) denotes the gradient operator.

At time \( t \) the zero level set \( \varphi = 0 \) describes the evolved of front. Thereby, \( \Gamma \) (t) (see Figure 2) deforms iteratively according to its normal direction with the speed function \( F \), and its position is given at each iteration step by the equation:

\[
\Gamma(x, y, t) = \{(x, y) | \varphi(x, y, t) = 0\} \quad \text{-----2}
\]

The initial function \( \varphi_0 \) is calculated based on the signed measure to the initial front \( \Gamma_0 \). It can be simply the Euclidean distance between one image point and the boundary the front. That is:

\[
\varphi_0(x, y) = \pm d((x, y), \Gamma_0) \quad \text{-----3}
\]
The sign of the distance \( d(x, y, \Gamma_0) \) is chosen such that the point inside the boundary has a negative sign and the one outside has a positive sign.

Now if we consider a unit circle in \( \mathbb{R}^2 \), in which it is shrinking itself with a constant rate, i.e. At each point on the boundary of the circle moves along its inwards pointing normal at some fixed speed.

The circle will shrink, and finally collapse down to a point.

C. Variational level set formulation of curve evolution without re-initialization

The standard re-initialization method is to solve the following initialization equation:

\[
\frac{\partial \phi}{\partial t} = \text{Sign}(\phi_0)(1 - |\nabla \phi|) \quad \text{---------4}
\]

Where \( \phi_0 \) is the function to be re-initialized, and \( \phi \) is the sign function. But problem is there if \( \phi_0 \) is not smooth or \( \phi_0 \) is much steeper on one side of the interface than the other, the zero level set of the resulting function \( \phi_0 \) can be moved incorrectly from that of the original function. For removing this limitation we use new approach of Variational Level Set Formulation of Curve Evolution without Re-initialization [7], [8]. The evolving level set function can deviate greatly from its value as signed distance in a small number of iteration steps, especially when the time step is not chosen small enough. So far, re-initialization has been extensively used as a numeric remedy for maintaining stable curve evolution and ensuring desirable results but re-initialization process is quite complicated, expensive and has subtle side effects. In Variational level set formulation, the level-set are dynamic curves that move toward the object boundaries. Therefore we define an external energy that can move towards the edges. If ‘I’ be the image, then edge indicator function \( g \) is defined by:

\[
g = \frac{1}{1 + |\nabla G_\sigma \ast I|^2} \quad \text{---------5}
\]

Where \( G_\sigma \) -Gaussian kernel with standard deviation \( \sigma \), we define an external energy for a function \( \phi \) (x, y) as below:

\[
E_g = \lambda \ell_g(\phi) + \alpha \ell_g(\phi) \quad \text{---------6}
\]

Where, \( \lambda > 0 \), and \( \alpha \) are constants, and the terms \( \ell_g(\phi) \) and \( \ell_g(\phi) \) are defined by

\[
\ell_g(\phi) = \int_{\Omega_g} \bar{g}(\phi) |\nabla \phi| dx dy \quad \text{---------7}
\]

\[
\ell_g(\phi) = \int_{\Omega_g} \bar{g}(\phi) |\nabla \phi| dx dy \quad \text{---------8}
\]

respectively, where \( g \) is the univariate Dirac Function, and \( H \) is the Heaviside Function. Now, the following total energy functional.

\[
E(\phi) = \mu P(\phi) + E_g, \lambda, \alpha(\phi) \quad \text{---------9}
\]

The external energy \( E_g \), drives the zero level set towards the object boundaries, while the internal energy \( \mu P(\phi) \) penalizes the deviation of from a signed distance function during its evolution which is given in equation given below:

\[
P(\phi) = \int_{\Omega} |\nabla \phi| - 1 |^2 dx dy \quad \text{---------10}
\]

The variational formula derives from the penalize energy equation:

\[
E(\phi) = \mu P(\phi) + Em \quad \text{---------11}
\]

Where, \( \mu > 0 \) is a parameter controlling the effect of penalizing the deviations of from a signed distance function, and \( Em(\phi) \) is a certain energy that would drive the motion of the zero level curve of \( \phi \). The energy functional \( Ag(\phi) \) introduced to speed up curve evolution. The coefficient \( \alpha \) of \( Ag \) can be positive or negative, depending on the relative position of the initial level-set to the object of interest. If the initial level-sets are placed inside the object, the coefficient \( \alpha \) should take negative value to speed up the expansion of the level-sets. By calculus of variations, the Gateaux derivative of the functional \( E \) in can be written as:

\[
\frac{\partial E}{\partial \phi} = -\mu \left[ \Delta \phi - \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) \right] - \lambda \delta(\phi) \text{div}(g) - \alpha \text{g} \quad \text{---------12}
\]

Where, \( \Delta \) is the Laplacian operator.

D. Implementation of Algorithm and Simulation

The algorithm was originally developed by Chuming Li [7] for his MATLAB code for level-set without reinitialisation. However the algorithm is complicated, expensive to implement and images result as obtained are also not smooth. The modified steps include specialized filtering methods used at various levels of image processing as in [8].

Step 1: Image acquiring and reading
Step 2: Initialize a level set function \( \phi \)
Step 3: Update local means
Step 4: Update local variances
Step 5: Update level set function \( \phi \)
Step 6: Return to step 3 until convergence criteria is met.
Step 7: Segmentation of image by Level set method

IV. RESULTS

The level set function \( \phi \) can be simply initialized as a binary step function as in [8], which takes a negative constant value -c0 inside the region \( \Gamma_0 \) and a positive constant value \( c_{outside} \) it. We choose \( c_0 = 2 \) in the experiments.
From fig (5) shows the tumor segmentation result of a brain image. In this case tumor boundaries are quite weak. Our method has also been applied to ultrasound images, which usually include speckle noise and low signal-to-noise ratio in 19.266547 seconds.

From fig (7) shows that boundaries of the ventricle are successfully delineated by our method despite the presence of strong noise in 25.838597 seconds.

V. CONCLUSION

The process of segmentation of medical images requires a very high degree of accuracy. The setup has been tested for a given set of medical images such as CT images and can also be used for X-rays and MRI images. In the process of final valuation, we found that the results using the variational level set segmentation techniques on CT images are better. In future if we combine multiple algorithms we can achieve better more accuracy in results.

VI. REFERENCES


VII. BIODATA

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