SEGMENTATION OF MEDICAL IMAGE USING GRADIENT WATERSHED AND FAST LEVEL SET METHODS

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ABSTRACT:

This paper proposes, a method modified Gradient image as input to the watershed transform algorithm this is compared with Fast Level Set method. The method is feasible in medical imaging and deserves. It could be used to segment the white matter, brain tumor and other small and simple structured organs in CT and MR images. In this paper used Gradient watershed transform and Fast Level Set method and compared their performance. We found that, improved segmentation as compared to traditional watershed and Segmentation of gradient watershed method is same as Fast Level Set method, but it consumes more time.

Keywords: Segmentation, Watershed transforms, Gradient, and fast level set method.

[1] INTRODUCTION

Brain tumors are two types one is primary tumor and second one is secondary tumor. The tumor cell is present within skull and grows within skull is called primary tumor. Malignant brain tumors are primary brain tumors. The tumor presents outside the skull and enter into the skull region called secondary tumor. Metastatic tumors are examples of secondary tumors [1]. Magnetic Resonance Imaging (MRI) is widely used in the scanning. The quality of image is high in the MRI. The quality of image is main important in brain tumor. MRI provides an unparallel view inside the human body [2-6]. The paper is processed on brain tumor MRI images for detection and Classification on different types of brain tumors [7-9]. We are going to use image processing techniques in this paper for detection of
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tumor from MRI images like histogram equalization, image adjustment, image segmentation are used for Detection of Tumor.

Watershed Transform

In geography a watershed is the ridge that divides areas drained by different river systems. A catchment basin means in this sense an area from which rainfall flows into a river or reservoir. The watershed transform applies these ideas to the gray-scale image processing to enable solution of a variety of image segmentation problems. Understanding the watershed transform requires us to consider a gray-scale image as a topological surface, where the values of f(x,y) are interpreted as heights. The watershed transform finds the catchment basins and ridge lines in such a grayscale image. In terms of the problem related to image segmentation the key concept is to change the starting image into another one whose catchment basins are the objects or regions.

[2] PROPOSED GRADIENT WATERSHED TRANSFORM

Watershed transformation is a powerful tool for image segmentation. In this paper, modified Gradient image as input to the watershed transform algorithm is used in segmentation is reviewed together with an abundant illustration of the methodology through examples of image segmentation coming from various areas of image analysis. There exists two basic ways of approaching image segmentation. The first one is boundary based and detects local changes. The second one is wavelet-based and searches for pixel. The gradient image is often used in the watershed transformation, because the main criterion of the segmentation is the homogeneity of the grey values of the object present in the image. But, when other criteria are relevant, other functions can be used. In particular, when the segmentation is based on the shape of the objects, the distance functions is very helpful. The impression which the current literature on watershed algorithms makes upon the initiated readers can only be of one great confusion.

Often it is uncertain exactly which definition for the watershed transform used. Sometimes the definition takes the form of the specification of the algorithm. A careful distinction between algorithm specification and implementation is in many cases lacking without such a separation correctness assessment of proposed algorithms is impossible. The watershed transform finds the catchment basins and ridge lines in such a grayscale image.

The Level Set Method
The segmentation problem reduces to finding curve(s) to enclose regions of interest. Intuitively, we can model the curves directly using control points. However, there are issues involved in updating the control points. For example, if two separate closed curves needed to merge into one, or one needs to split into two, when would this merge/split take place? How would an algorithm detect when to merge or split? After this is detected, data structures for the curve would then needed to be updated as well. If control points are too close together, how should they be merged? There are solutions to these difficulties [13]. However, these issues can all be alleviated using the level set method. The level set method was first presented by Osher and Sethian for front propagation, being applied to models of ocean waves and burning flames [13]. Malladi applied it for medical imaging purposes [12]. The idea behind the level set method is to imbed a curve within a surface. In our case, we imbed a two dimensional curve within a three-dimensional surface.
[3] METHODOLOGY

In this section, we will describe how the level set method is formulated [12]. We define the segmentation boundary as part of a surface where the contour level is 0, i.e., the zero level set. Let $\varphi$ represent the implicit surface such that $\varphi(x, t) = \pm d$ where $x$ is a position in our domain (the image), $t$ is time, and $d$ is the distance between position $x$ and the zero level set. The sign in front of $d$ is positive if $x$ is outside zero level set. Otherwise, the sign is negative. Note that the curve of interest is then marked by positions where $\varphi = 0$.

To evolve $\varphi$ over time, use the chain rule:

$$\varphi_t + \varphi_{xxt} + \varphi_{ytt} = 0 \quad (1)$$

$$\varphi_t + (x_t, y_t) \cdot \nabla \varphi = 0.$$

Now, let $(x_t, y_t) = n+s$ where $n$ is the vector normal to the front at point $x$ and $s$ is some arbitrary vector. Note that since $n$ and $s$ are defined over the entire domain of $x$, they are actually vector fields. The above equation can then be written as

$$\varphi_t + (n + s) \cdot \nabla \varphi = 0$$

$$\varphi_t + n \cdot \nabla \varphi + s \cdot \nabla \varphi = 0$$

$$\varphi_t + V_n \| \nabla \varphi \| + s \cdot \nabla \varphi = 0 \quad (2)$$

Where $V_n$ is some scalar [10]. The two values, $V_n$ and $s$, can be viewed as two independent forces that evolve the surface. The scalar $V_n$ will control how fast the surface will move in the normal direction. The vector $s$ will be another force that dictates both direction and speed of evolution. The partial differential equation can then be solved when provided an initial condition, $\varphi(x, t = 0)$. Thus, the segmentation problem reduces to an initial value problem. This is the formulation used in the implementation presented within this report.

The Fast Marching Method imitates this process. Given the initial curve (shown in red), stand on the lowest spot (which would be any point on the curve), and build a little bit of the surface that corresponds to the front moving with the speed $F$. Repeat the process over and over, always standing on the lowest spot of the scaffold, and building that little bit of the surface. When this process ends, the entire surface has been built.

Fig.1: Construction of stationary level set solution Green squares show next level to be built

The speed from this method comes from figuring out in what order to build the scaffolding; fortunately, there are lots of fast sorting algorithms that can do this job quickly. The main idea of level set method is to represent a closed curve $\Gamma(t)$ on the plane as the zero
level set of a higher dimensional function $\Phi$. The motion of the curve is then embedded within the motion of the higher dimensional surface. Let $\Gamma(t)$ be the closed sign is chosen if the point $x$ is outside (inside) the initial front $4\Gamma(0)$ [14]. An Eulerian formulation is produced for the motion of this surface propagating along its normal direction with speed $F$, where $F$ can be a function of the surface characteristics (such as the curvature, normal direction etc.) and the image characteristics (e.g. the gray level, gradient etc.).

The equation of the evolution of $\Phi$, inside which our surface is embedded as the zero level set is then given by the following equation.

$$\Phi_t + F \nabla \Phi = 0 \quad (3)$$

The major advantages of using this method over other active contour strategies include the following [15].

First, the evolving level set function $\Phi(x, t)$ remains a function, but the propagating front $\Gamma(t)$ may change topology, break, merge and form sharp corners as $\Phi$ evolves. Second, the intrinsic geometric properties of the front may be easily determined from $\Phi$. For example, at any point of the front, the normal vector is given by $n = \nabla \Phi$. Finally, the formulation is unchanged for propagating interfaces in three dimensions.

One of the most popular level set algorithms is the so-called fast marching method.

Now consider the special case of a surface moving with speed $> 0$ (the case where $F$ is everywhere negative is also allowed). We then have a monotonically advancing front whose level set equation is of the following form:

$$|\nabla T|F = 1 \quad (4)$$

There are two ways of approximating the position of the moving surface: iteration towards the solution by numerically approximating the derivatives in Eq. (1) or explicit construction of the solution function $T$ from Eq. (2). Fast marching method depends on the latter approach.

Equation (2) is one form of the Eikonal equations. Sethian proved that it is equivalence to solve the following quadratic equation in order to get the arrival time $T$ of the Eq. (2).

The steps of the traditional fast marching method are as follows:

1. **Initializing step:**
   a) *Alive points:* Let $A$ be the set of all grid points $\{(iA, jA)\}$ which represents the initial curve.
   b) *Narrowband points:* Let Narrowband points be the set of all grid point neighbors of $A$. In our Algorithm, those are the 4-nearest points of the seeded points. Set
   $$T(x, y) = 1/F(x, y). \quad (5)$$
   c) *Faraway points:* Let Faraway points be the set of all others grid points $\{x, y\}$. Set $T(x, y) = \text{TIME MAX.}$

2. **Marching forwards:**
   a) Begin loop: Let $(i\text{min}, j\text{min})$ be the point in Narrowband with the smallest value for $T$;
   b) Add the point $(i\text{min}, j\text{min})$ to $A$; remove it from Narrowband;
   c) Tag as neighbors any points $(i\text{min} - 1, j\text{min}), (i\text{min} + 1, j\text{min}), (i\text{min}, j\text{min} - 1), (i\text{min}, j\text{min} + 1)$ that are either in Narrowband or Faraway. If the neighbor is in Faraway, remove it from that list and add it to the set Narrowband;
   d) Recomputed the values of $T$ at all neighbors according to equation 3, selecting the largest
possible solution to the quadratic equation;
e) Return to top of Loop.

Level set Method

The main characteristic of the level set method is its ability to pick up the right topology of the shape we are segmenting. The accuracy of the segmentation process depends upon where and when the propagating hyper surface needs to stop. For the fast marching method, the segmentation results rely on the definition of speed function to a greater degree. Whether the speed function adopts the definition of there is a tunable parameter α or β which determines the value of speed function. It is important and also difficult to select the adaptive parameter value. So, on the condition of specified parameter value, it is necessary to use level set method to finely tune the rough contours obtained from fast marching method. In addition, through fast marching method, we can get the rough front and the location of each pixel. That is, we can determine where each pixel locates. It is useful and convenient to calculate the signed distance of the following level set method which is from each pixel to the front boundary.

The application of level sets in medical segmentation of medical imagery becomes extremely popular because of its ability to capture the topology of shapes in medical imagery. Since the proposal of level set method, many researchers have succeeded in applying level set method to image processing and computer vision. The motion equation of level set method is given by.

1. Problems of traditional level set methods
   a) High computational complexity of solving the PDE (Unnecessary sub pixel accuracy)

2. To accelerate: avoid solving of the PDE
   a) Discrete representation, as simple as possible of the boundary
   b) Simplify the velocity field
   c) Reduce complexity of operations.

The fast level set method

Level set method contains many good mathematical properties which make it an accurate description for front propagation. For image segmentation, the level set method has the ability to handle objects with topology changes from the initial contour. This paper presents a fast level set method which keeps this advantage at a much reduced computational time.

[4] IMPLEMENTATION

Let the interface is represented by 2 neighboring sets of grid points: Lin Lout
 Roughly approximates the signed distance function

\[ \Psi(X) = \begin{cases} 
3 & \text{if } X \text{ is an exterior point } (X \in \Omega \triangle X \in Lout) \\
1 & \text{if } X \in Lout 
\end{cases} \]
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-1 if \( X \in \text{Lin}; \\
-3 \text{if } X \text{ is an interior point } (X \in \Omega \setminus X \cap \text{Lin}); \\

1) Velocity Field \( V \) Reflects only the image based external force Positive for a foreground image pixel and vice-versa uses a modified Chan-Vese segmentation criterion

\[
V(X) = \begin{cases} 
1 & \text{if } -\lambda_1 ((f(x) - C_1)^2 + \lambda_2 (f(x) - C_2)^2) \geq 0; \\\n-1 & \text{if } -\lambda_1 ((f(x) - C_1)^2 + \lambda_2 (f(x) - C_2)^2) < 0; 
\end{cases}
\]

1) Interface Smoothing
   a. Gaussian smoothing of the level set function \( \Psi \)
   b. Gaussian filtering of \( \Psi \) is calculated only at \( \text{Lin} \) and \( \text{Lout} \) points
   c. NEW: we use an anisotropic Gaussian filter \( G \)
   d. The boundary is updated, if \((G * \Psi'(x)) * \Psi'(x) < 0\)

[Iteration and Control]

Each major iteration consists of \( \text{Ne} \) evolution steps followed by \( \text{Ng} \) smoothing steps

a. \( \text{Ne} \) controls the penetrability of the evolving interface
b. \( \text{Ng} \) controls the amount of smoothing
c. Two stopping criteria:
d. Maximum number of major iterations
e. NEW: maximum number of boundary pixels changing state between major iterations

[Proposed Algorithm]

a. Compute the velocity field \( v \);
b. Create the Gaussian mask \( G \);
c. Create the \( \text{Lin} \) and \( \text{Lout} \) from \( \psi \);
d. While the stopping criterion is not reached do: for \( i = 1 \) to \( \text{Ne} \) do:
   - Outward evolution;
   - Eliminate redundant points in \( \text{Lin} \);
   - Inward evolution;
   - Eliminate redundant points in \( \text{Lout} \); for \( i = 1 \) to \( \text{Ng} \) do:
   - Outward interface smoothing; Eliminate redundant points in \( \text{Lin} \); Inward interface smoothing; Eliminate redundant points in \( \text{Lout} \).
e. Return final \( \psi \)

[Advantage]

a. Preserves all advantages of traditional level set methods
b. Discrete approach
c. The zero level set representation using a list of boundary points
d. Avoids computing any PDE
e. Regularization handled by a separate step of the algorithm

[Algorithm]

Different approaches may be employed to use the watershed principle for image segmentation
a. Local minima of the gradient of the image may be chosen as markers, in this case an over-segmentation is produced and a second step involves region merging.
The key of fast marching method is the definition of speed function, due to the fact that speed function only depends on the gradient information (edge information) not the global information of the image region, it is easy to make mistakes in segmenting the blurred image boundary.

In general it is well known that the image is composed of many small regions. Each region is of homogeneity. Such as the contiguous intensity value, the similar texture structure. It is crucial for the final segmentation result to make full use of the region information. So we introduced watershed transform to over segment the original image into many small regions.

The merit of introducing gradient watershed transformation lies in three aspects. Firstly, for fast marching method, let the initial contour region be the seeded point the segmentation accuracy can be improved since the final segmentation results are bounded to be potential boundaries of objects. Finally the statistical similarity degree of the nearby regions is a good reference of speed function of fast marching method.

[5] EXPERIMENTAL DETAILS

The proposed system efficiently classifies the MRI brain tumor images. The tumor is isolated from the MRI brain images by using Gradient Watershed Transform. The Classification of MRI brain tumor images are also successfully implemented by using Fast Level Set method. The proposed system efficiently classifies the brain tumor MRI images into different grades.

The following figures show that the segmentation using gradient watershed transforms and Fast Level Set Method. Excellent segmentation results were obtained for texture images as well as medical images with the Texture Gradient Watershed method. A minimum region size for local minima controlled by minsize parameter determines the number of local minima regions for marker image. By suitably choice of the minimum region size, over segmentation is controlled to a large extent. The results show that the segmentation implemented through Gradient Watershed method is superior to the others methods and it performs equally well with respect to Fast Level Set Method segmentation.
[6] CONCLUSION AND FUTURE SCOPE

This paper has been devoted to study the problem of image segmentation and to propose algorithms to solve it. Gradient Watershed transform method was chosen to introduce new efficient segmentation methods for medical images with textures. The main reason is that this model offers a rigorous mathematical framework. The results show that the segmentation implemented through Gradient Watershed method is superior to the others methods and it performs equally well with respect to Fast Level Set Method segmentation.

In the future, we will integrate watershed transform and level set method with statistical shape analysis to make it applicable to more kinds of medical images and have better robustness to noise.
REFERENCES


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