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DETECTION OF BRAIN TUMOUR USING A HYBRID SEGMENTATION MODEL BASED ON WATERSHED AND FLUID VECTOR FLOW

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ABSTRACT

Medical Image segmentation deals with segmentation of tumor in CT and MR images for improved quality in medical diagnosis. Fluid Vector Flow (FVF) enhances the concave object extraction capability. We propose a new approach that we call the “fluid vector flow” active contour model to address problems of insufficient capture range and poor convergence for concavities. This paper intends to combine watershed algorithm with FVF snake model to reduce the computational complexity, to improve the insensitiveness to noise, and capture range. Specifically, the image will be segmented firstly through watershed algorithm and then the edges produced will be the initial contour of FVF model. This enhances the tumor boundaries and tuning the regulating parameters of the FVF snake mode by coupling the smoothness of the edge map obtained due to watershed algorithm. Superiority of the proposed work is observed in terms of capture range, concave object extraction capability, sensitivity to noise, computational complexity, and segmentation accuracy.

KEYWORDS: Image segmentation, Watershed transform, and Fluid Vector Flow.

INTRODUCTION

Image segmentation technique plays crucial role in medical imaging by facilitating the delineation of regions of interest. There are numerous techniques in medical image segmentation depending on the region of interest. Thresholding is the most basic one; it is based on separating pixels in different classes depending on their gray level. In medical imaging, several variations of this approach incorporating local intensities or connectivity are proposed. In this case, the gray level between tumor and muscles is very close, so this technique is difficult to apply. Classifiers often use features in order to train for regions of interest recognition. But, in this case, the great variability in shape and gray level of tumors is very difficult to characterize. Clustering techniques, viz., are interesting methods classifying pixels in an extracted features space but they are sensitive to noise therefore, this method is not directly adapted to noisy MR images. Recently, Deformable models and Watershed transform methods are efficient for medical image segmentation. Active contour models or snakes have been adopted as effective tools for segmentation and object tracking. Active contour models discussed in the literature can be classified into two categories: parametric and level set.

RELATED WORK

Important issues concerning fundamental aspects of image segmentation methods viz., initialization, convergence, ability to handle topological changes, stopping criteria and over segmentation must be taken into account. Segmentation by Deformable models uses image forces and external constraints to guide the evolution. Former versions of this method require the initialization to be done close to the boundaries of the objects, to guarantee proper convergence. Modeling the contours in the level set framework easily solves the topological problem, but do not address the initialization and convergence issues. Fluid Vector Flow active contour model to address problems of insufficient capture range and poor convergence for concavities. Watershed transform treats the image as a 3D surface, starts the region growing from the surface minima. However it may lead to a strong over-segmentation if proper image smoothing is not provided. The marker controlled watershed transform overcomes the over-segmentation problem up to some extent. However, highly specialized filters are required to extract the markers. To overcome these shortcomings, recently hybrid models are proposed. In this paper, a new hybrid model for segmentation of brain tumors from MR images is proposed. It is aimed to

increase the capture range to the image border and to improve the concave object extraction capability. This proposed method substantially reduces the above mentioned problem of convergence in noisy images and computational complexity. Superiority of the proposed work is observed in terms of capture range, concave object extraction capability, sensitivity to noise, computational complexity and segmentation accuracy.

BACKGROUND

3.1 WATERSHED TRANSFORM

Assume that the image f is an element of the space $C(D)$ of a connected domain D then the topographical distance between points p and q in D is,

$$T_F(p, q) = \inf_{\gamma} \int \|\nabla f(\gamma(s))\| ds$$

where, 'inf _{γ} ' is over all paths (smooth curve) inside D , based on Roerdink. defines the watershed as follows.

Let $f \in C(D)$ have a minima $\{m_k\}_{k \in I}$, for some index set I . The catchment basin $CB(m_i)$ of a minimum m_i is defined as the set of points $C \in D$, which are topographically closer to m_i than to any other regional minimum m_j . The watershed of f is the set of points which do not belong to any catchment basin.

$$W_{shed}(f) = D \cap \left(\bigcup_{i \in I} CB(m_i) \right)$$

The watershed transform is the method of choice for image segmentation in the field of mathematical morphology has proven to be a powerful and fast technique for both contour detection and region-based segmentation. However, recent progress allows a regularization of the watershed lines with an energy-based watershed algorithm (water snakes). The proposed work is based on FVF snake which easily allow a regularization of the watersheds. The advantage of the watershed transform is that, it produces closed and adjacent contours including all image edges. However, often the watershed produces a severe over segmentation also. Some solutions of the over-segmentation are addressed in the marker-controlled watershed segmentation has been shown to be a robust and flexible method for segmentation of objects with closed contours, where the boundaries are expressed as Markers are placed inside an object of interest; internal markers associate with objects of interest, and external markers associate with the background. After segmentation, the boundaries of the watershed regions are arranged on the desired ridges, thus separating each object from its neighbors.

3.2 FLUID VECTOR FLOW (FVF)

Fluid vector flow which simulates fluid flowing along the object boundary and generates an external force field dynamically to drive the contour evolution. FVF has the largest capture range, i.e., the entire image. FVF is also able to extract acute concave shapes due to its non-static external force fields. In this model, the external force field changes dynamically with the contour evolution. Thus, the FVF contour does not get stuck and acute concavities can be extracted. This method is executed in three stages: binary boundary map generation, vector flow initialization, and FVF computation.

A. Binary Boundary Map Generation

In the first stage, we apply a Gaussian smoothing filter to the input image and apply a gradient operator to find edges in the image. A threshold (free parameter) $T \in [0, 1]$ is then used to generate the binary boundary map.

B. Vector Flow Initialization

At this stage, the contour should be initialized to initialize the external force field. The initial parametric contour can be initialized either inside, outside, or overlapping the target object. The FVF method is insensitive to the initialization by taking advantage of the binary boundary map generated at the previous stage.

C. FVF Computation

The initial forces will push the active contour to the neighborhood of the target object. At the last stage, a control point is automatically selected from the object boundary and generates new external force field to evolve the active contour. This point can flow freely along the object boundary like a drop of fluid, dynamically update the external force field to avoid the problem of saddle points and stationary points, and thus further evolve the active contour until convergence is achieved.

THE PROPOSED HYBRID MODEL

The algorithm proposed in this paper belongs to the category of hybrid techniques, since it results from the integration of edge and region-based techniques through the morphological watershed transform. This algorithm delivers accurately localized and closed object contours while it requires a small number of input parameters). Initially, the noise corrupting the image is reduced by a noise reduction technique that preserves edges remarkably well, while reducing the noise quite effectively. At the second stage, this noise suppression allows a more accurate calculation of the image gradient and reduction of the number of the detected false edges. Then, the gradient magnitude is input to the watershed

detection algorithm, which produces an initial image tessellation into a large number of primitive regions.

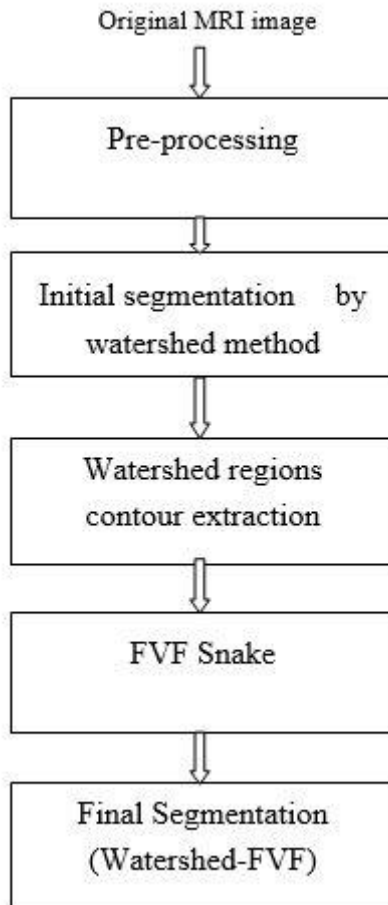
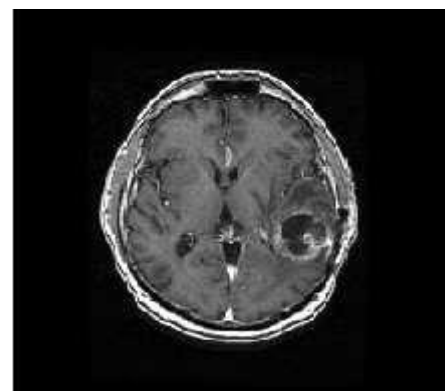


Figure 1. Flow diagram of the proposed segmentation algorithm (hybrid model)

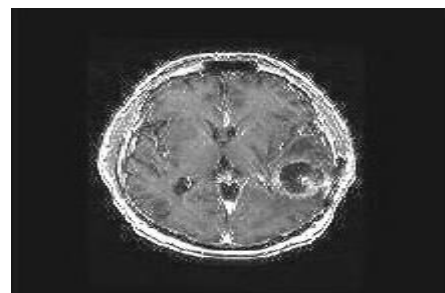
This initial over-segmentation is due to the high sensitivity of the watershed algorithm to the gradient image intensity variations, and, consequently, depends on the performance of the noise reduction algorithm. Over-segmentation is further reduced by markers, i.e., gradient magnitudes prior to the application of the watershed transform. The output of the watershed transform is the starting point of a bottom-up hierarchical merging approach. Figure1 illustrates the proposed hybrid segmentation algorithm. This method consists of different modules. Before carrying out segmentation, the MR image must undergo a preprocessing step to avoid the over segmentation. The second module is the Watershed transform based on the concept of marker controller, deals with the immersion principles, applied to a topographic image representation to extract watershed region contours. Those contours will constitute the initial

FVF snakes that will deform to capture the target edges. The last part combines the Watershed and FVF to segment tumor from brain MR image, i.e., coupling the smoothness of the edge map to the initial size of the FVF snake by automatic initialization of contour in order to preserve a limited number of suspect areas. FVF snakes have a large capture range so correct snake deformation can be achieved even if the contour of the watershed region is far away from the target edges. So, FVF snake is most suitable to drive the watershed contours towards tumor boundaries.

EXPERIMENTAL RESULTS AND DISCUSSION



(a)



(b)



(c)

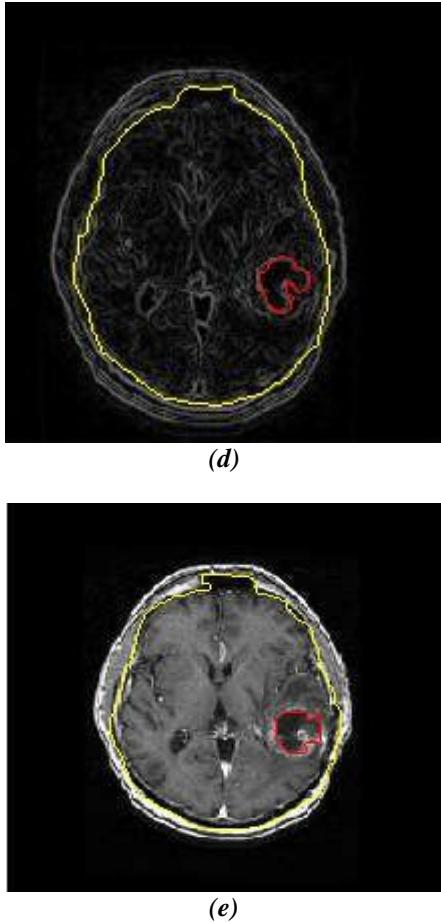


Figure2. Segmentation using proposed hybrid model.

- (a) Original image,
- (b) Watershed segmentation
- (c) Gradient image
- (d) Watershed regions
- (e) Segmentation using Watershed and FVF

The proposed segmentation strategy is presented in Figure.2. Fig. 2(a), 2(b), and 2(c) correspond to original MR image having brain tumor, watershed, and gradient image respectively. Watershed regions, after applying marker-controlled watershed algorithms are shown in fig. 2(d). The final segmentation combining watershed and FVF is as shown in fig. 2(e).

CONCLUSIONS AND FUTURE WORK

In this paper, hybrid segmentation model combined with FVF snake and marker controlled watershed is introduced to segment the brain tumor. Real MR images are used for the validation of the proposed framework. The proposed method gives robust contour that converges to boundaries of tumors of different sizes in very noisy images. The experimental results show that the algorithm is able to

speed up the process considerably while capturing the desired object boundary compared to other methods. Future work includes by treating the image as a 3D time-dependent surface and selectively deforming this surface based on variation approaches.

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