



PDE on Medical Image Processing

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Abstract: In Medical images edge detection and enhancement is an essential requirement for object recognition. Active Contour models are an attractive approach to boundary detection in medical images. Over the last ten years, numerous methods have been developed within different theoretical framework for edge detection.

Edge detection is a fundamental step in Medical image processing, Edge detection significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image .Edge detection is in the forefront of image processing for object detection, it is crucial to have a good understanding of edge detection algorithms. In this paper the parametrical equations governing the so called snake, which is an active contour model is introduced. Active contours or snakes use completely different approaches to feature extraction. In Active contour a set of points are enclosed to get a target feature. First, an initial contour is placed outside the tumour The contour is then minimized to find a new contour which shrinks so as to be closer to the tumour.

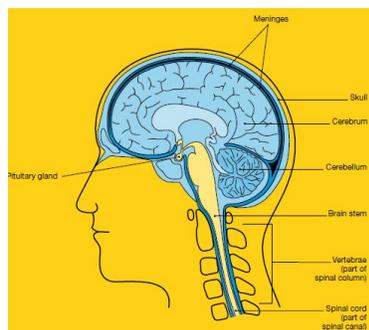
A comparison of Active Contours, are made to find out their suitability to particular type of medical images. This study shows that active contours are best in presence of concave boundary medical images.

Key words: Active contour models, Bending Energy, deformable surface models, Elastic Energy, External Forces, gradient vector flow, image segmentation, Kass Model.

INTRODUCTION

The brain is the most important organ in the body. It controls all voluntary and involuntary processes, such as learning, sensing, imagining, remembering, breathing, blood circulation and heart rate, etc.

The main sections of the brain are the cerebrum, cerebellum and the brain stem. These parts play unique roles in the body's functions, many of which are essential to staying alive. Deep within the brain is the pituitary gland. It controls growth and development by releasing chemical messengers (hormones) into the blood. These signal other hormones to start or stop working.



The Cerebrum

The Cerebrum is the upper part of the brain. It is dome-shaped and is the largest part of the brain. The cerebrum controls our thinking, our learning ability, memory and basic intelligence. It also controls our sense organs.

The cerebellum

It is the lower part of the brain.it is much smaller than the cerebrum. Cerebellum is located towards the back of the brain. It controls the muscle movement and helps us to keep our balance.

The Brain Stem

All basic life functions originate in the brain stem, including heartbeat, blood pressure and breathing. The brain stem consists of midbrain, pons and medulla. The right half of the brain controls the left side of the body. Similarly the left half of the brain controls the right side of the body. Thus when one side of the brain is damaged, the opposite side of the body gets affected.

Tumour

Cancer is a disease of the cells, which are the body's basic building blocks. Our bodies constantly make new cells to help us grow, to replace worn-out cells and to heal damaged cells after an injury. Normally cells grow and multiply in an orderly way, but sometimes something goes wrong with this process and cells grow in an uncontrolled way. This uncontrolled growth may result in abnormal blood cells or may develop into a lump called a tumour. A tumour can be **benign** (not cancer) or **malignant** (cancer). A benign tumour is contained in one area and does not spread to other parts of the body. Most benign brain tumours are slow growing and unlikely to spread, even throughout the brain. In brain tumor analysis, segmentation of abnormal tissues, anatomical structures and pathologies from MRI in particular, plays a predominant role. The results from this segmentation are the foundation for further analysis. It is necessary to change the segmentation methods depending on the hard and soft tissues and image modalities. In addition to, segmentation of MR brain images is a daunting task because they generally involve a large amount of data.

Snakes, or active contours, are used extensively in computer vision and image processing applications, particularly to locate object boundaries. Problems associated with initialization and poor convergence to boundary concavities. Active contours are curves defined within an image domain that can move under the influence of internal forces coming from within the curve itself and external forces computed from the image data. The internal and external forces are defined so that the snake will conform to an object boundary or other desired features within an image. There are two general types of active contour models in the literature today: **Parametric active contours** and **Geometric active contours**. In this paper we focus on parametric active contours.

Parametric active contours synthesize parametric curves within an image domain and allow them to move toward desired features, usually edges. Typically, the curves are drawn toward the edges by potential forces, which are defined to be the negative gradient of a potential function. Additional forces, such as pressure forces [10], together with the potential forces comprise the external forces. There are also internal forces designed to hold the curve together (elasticity forces) and to keep it from bending too much (bending forces)..

Proposed Algorithm

Step 1: Read the MRI brain image.

Step 2: Apply K-Means algorithm in order to extract the tumor region.

Step 3: The tumor region obtained in the step 2, is to be defined as initial contour for snakes method.

Step 4: Use the initial contour which is defined in the step 3 of the methodology in order to obtain final tumor contour, by snakes.

Step 5: Automatically points are defined by the system in order to obtain final counter.

Step 6: Comparison of all the snake methods.

Implementation Flow

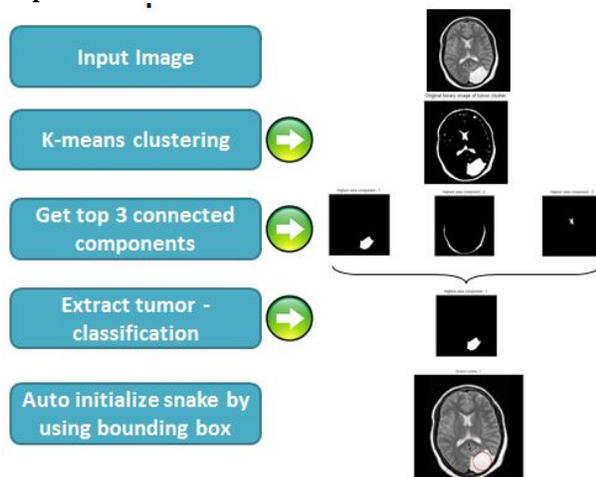


Fig 1 shows the implementation flow, extraction of tumor and contour which shrinks closer to the tumour.

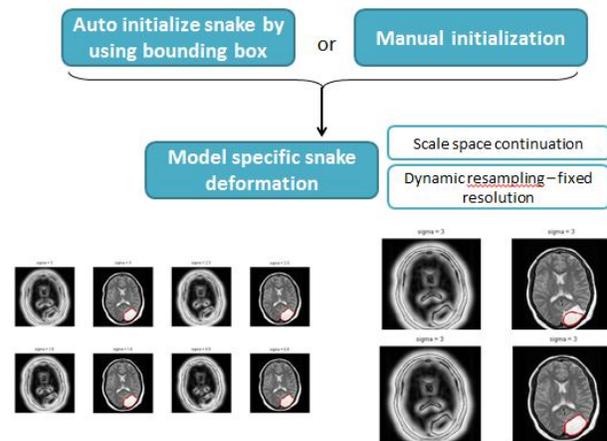


Fig 2 shows the Auto Initialize of snake using Bounding Box

Parametric Snake Model:

A traditional snake is a curve that moves through the spatial domain of an image to minimize the energy functional

$$\frac{\partial}{\partial s} \left(\alpha(s) \frac{\partial u}{\partial s} \right) - \frac{\partial^2}{\partial s^2} \left(\beta(s) \frac{\partial^2 u}{\partial s^2} \right) + \overline{F_{ext}} = 0 \quad (1)$$

Active contours are contours that deform/evolve continuously under image forces and internal elasticity, rigidity. Image energy/force is computed from the image itself Image energy is formulated in such a manner so as to make image energy minimum (or zero force) at the edges,

$$E_{img} = -|\nabla(G_{\sigma} * I)|^2 \quad (2)$$

where weighting parameters that control the snake's tension and rigidity respectively. The external energy function is derived from the image so that it takes on its smaller values at the features of interest, such as boundaries.

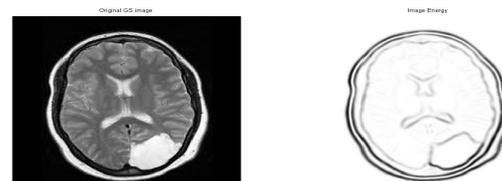


Fig 3 shows the Energy Map.

K-means clustering

- In this clustering technique, 'k' describes the number of desired clusters.
- Clustering is achieved by finding the equilibrium centroids (i.e., after iterations, the final centroid values)
- Pixels belonging to a particular cluster are closer to the centroid of that cluster
- In the brain images that we studied, we observed that k=3 gives us the tumor in 3rd cluster

TH1 values are the mean of centroids and in our case, we need to find the end TH1 i.e., TH2

TH2 can be used to threshold the image to get only the cluster containing the tumor (cluster 3 as shown in the figure)

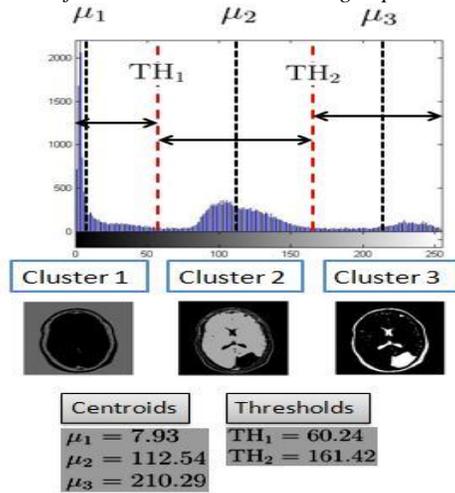


Fig 4 shows the tumor in 3rd cluster
 Erode the tumor cluster (to remove any small connections)
 Get the 3 highest area connected components
 Tumor extraction is done by two parameters, area and area density.

VARIOUS MODELS USED

Depending on the external force three different models can be defined:

Kass Model

The snakes were first introduced by Kass et al in 1987. It represents the object boundary as a parametric curve. An energy function E is associated with the curve. The objective is to minimize the energy to lock the object boundary with the object. A parametric curve is defined as an equation:-

$$\bar{F}_{ext,kass} = -\bar{\nabla}E_{img} \tag{3}$$

Balloon Model

The snake’s model introduced by Kass was revised by Lauren D. Cohen and named the new model as Balloon model. The Kass model based on the principle that the parametric curve would shrink when not under the influence of image forces, where as the Cohen Snake expands. The expansion of snake resembles the shape of balloon i.e. why the model named to Balloon Snake.

$$\bar{F}_{ext,balloon} = k_1 \hat{n} - k \frac{\bar{\nabla}E_{img}}{\|\bar{\nabla}E_{img}\|} \tag{4}$$

GVF Model

GVF Force has larger capture range due to the regularizing effect. However, GVF force is relatively more smeared as compared to Kass force. Hence we will implement scale-space continuation i.e., decrease sigma in steps. The basic model is identical to that proposed by Kass. However, GVF Snake is associated with a new kind of external field that is a vector force field. So the difference in algorithm is only in the way this external field is calculated.

The gradient vector flow is defined as, $v(x,y) = (u(x,y),$

$v(x,y))$ that minimizes the energy function.

$$\bar{F}_{ext-gvf} \equiv \bar{G} = [u, v] \tag{5}$$

$$\mu \nabla^2 u - (u - f_x)(f_x^2 + f_y^2) = 0 \tag{6}$$

$$\mu \nabla^2 v - (u - f_y)(f_x^2 + f_y^2) = 0 \tag{7}$$

Edgemap

$$f(x, y) = -E_{img} \tag{7}$$

$$f_x = \frac{\partial f}{\partial x}, f_y = \frac{\partial f}{\partial y}$$

μ - Regularizing parameter

Solving this would provide u,v and hence the GVF force.

Greedy Model:

A model for representing image contours in a form that allows interaction with higher level processes has been proposed by Kass et al. In this paper we present some of the problems in both methods and propose a further algorithm which is stable, is flexible, allows hard constraints, enhance much faster than the dynamic programming methods .In the method a presented here a different formulation is used for continuity term so that the points will be more evenly spaced on three contour rather than minimizing distance between points as in the previous methods.

$$E_{snake} = \int_0^1 [\alpha(s)E_{cont} + \beta(s)E_{curv} + \gamma(s)E_{img}] ds \tag{8}$$

$$E_{count} = \left| \bar{d} - \left| \bar{u}_i - \bar{u}_{i-1} \right| \right| \tag{9}$$

$$E_{curv} = \left| \bar{u}_{i-1} - 2\bar{u}_i + \bar{u}_{i+1} \right|^2 \tag{10}$$

$$E_{img} = -\left| \bar{\nabla}(G\sigma * I) \right|^2 \tag{11}$$

RESULTS AND DISCUSSION

Kass Model Results:



Fig 5 shows Initial contour for Kass Model and Final contour of proposed method. The Error Measures represent the best quantitative result.

Balloon Model Results:



Fig 6 shows Initial contour for Balloon Model and Final contour of proposed method. The Error Measures represent the best quantitative result.

Greedy Model Results:

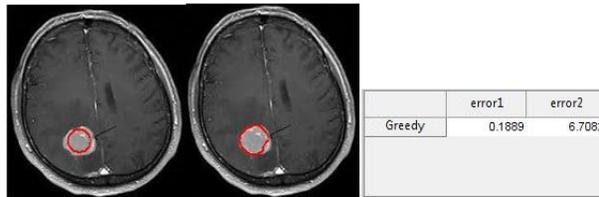


Fig 7 shows Initial contour for Greedy Model and Final contour of proposed method. The Error Measures represent the best quantitative result.

GVF Model Results:

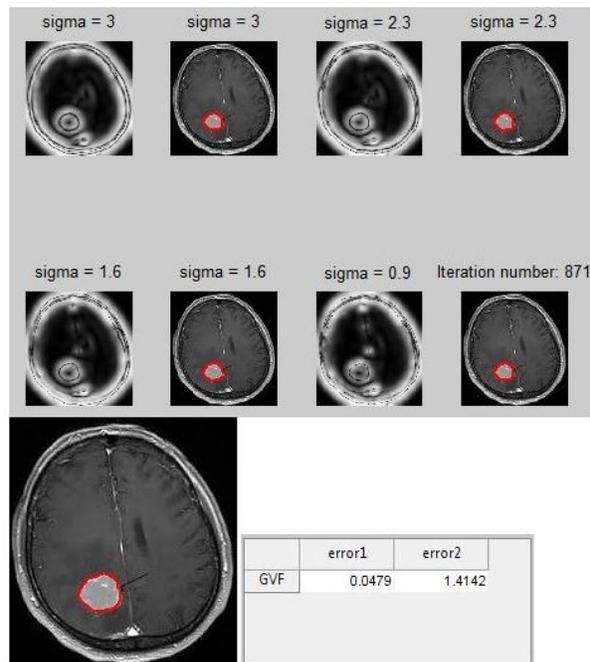


Fig 8 shows Initial contour for GVF Model and Final contour of proposed method. The Error Measures represent the best quantitative result.

Discussion

“Snake” parameters are sensitive to the type of image and the parameters depend on the contrast level of the image, noise, edge strength etc. GVF force depends on regularizing parameter and number of iterations. From the extracted results of proposed methodology of the tumor it is observed that GVF are better than other snake methods.

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