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The Importance of Edge Detection for Brain Tumor Using Snake Algorithm

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Abstract – Medical imaging allows scientist and physicians to decide about life saving information regard to the human physiological activities. It plays an important role in the diagnosis, therapy and treatment of various organs, tumors and other abnormalities. There are more than 120 types of brain tumors; Brain tumors contain all tumors inside the cranium or in the central spinal canal. They are produced by an abnormal and uncontrolled cell division, normally either in the brain itself (neurons, glial cells (astrocytes, oligodendrocytes, ependymal cells, myelin-producing Schwann cells), lymphatic tissue, blood vessels), in the cranial nerves, in the brain envelopes (meninges), skull, pituitary and pineal gland, or spread from cancers primarily located in other organs (metastatic tumors). Any brain tumor is naturally serious and dangerous because of its invasive and infiltrative character in the limited space of the intracranial cavity

Keywords: Edge, Detection, Brain, Tumor, Snake

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INTRODUCTION

Brain tumors or intracranial neoplasms can be cancerous (malignant) or noncancerous (benign); however, the definitions of malignant or benign neoplasms differs from those commonly used in other types of cancerous or noncancerous neoplasms in the body. Its threat level depends on the combination of factors like the type of tumor, its location, its size and its state of development. Because the brain is well protected by the skull, the early detection of a brain tumor only occurs when diagnostic tools are directed at the intracranial cavity. Usually detection occurs in advanced stages when the presence of the tumor has caused unexplained symptoms. Image segmentation is typically used to locate objects and boundaries in images and should stop when the object of interest in an application have been isolated.

Parametric snakes are described by an objective function that consists of three parts the internal energy of the snake, the image energy and external energies. One approach is to formulate the internal energy of the snake by using the (weighted) first and second derivatives of the curve. The first derivative term is indicative of the “elasticity” of the snake, in that it penalizes points that move away from each other. The second derivative term is a measure of the stiffness of the snake, viz., how strongly it resists bending.

The image energy term determine what features of the image the snake seeks, e.g., edges, lines and terminations. The image energy term is chosen so that it minimizes the energy at the features where the snake is expected to converge. For example, in a binary edge image, the pixel intensity can be a good term for the image energy.

A snake is an energy minimizing parametric curve, C, represented by the vector v(s) = (x(s), y(s)), where x and y are coordinate functions of s, the normalized arc length. s[0, 1] is the parametric domain. in this paper we will be dealing exclusively with closed curves so C (0) = C (1). To conform to the boundary of an object it is placed in proximity to, a snake works by minimizing an associated energy functional. The energy functional associated with the snake can be viewed as the representation of the energy of the snake and the final snake corresponds to the minimum of this energy. A snake conforms to the boundary of an object by deforming its shape and moving through the spatial domain of the image until it reaches a location (theoretically the object’s boundary) where its energy functional is at a minimum.

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Compared with the original snake, the external force field on the image is constructed also as the negative of the external energy gradient, which is the distance from each point to its closest edge points in the image. The new external energy enables a large magnitude for the external force everywhere in the image. Thus, the distance snake has a large capture range, i.e., the initial contour can be located far away from the desired boundary if there are no spurious edges along the way. By using a finite element method, the deformable contour is represented as a continuous curve in the form of weighted sum of local polynomial basis functions.

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The goal of the Brain tumor image (fig. 1) was to determine which method could better segment tumor. The test images are at different sizes and resolutions. Included are also images with added noises (Gaussian, salt and pepper) corrupting the overall quality of the images Fig.1. Although these types of noise are normally modality dependent or not present due to the high quality of today's imaging devices, it is still interesting to show the performance of the methods in the presence of different types of noise.

We add noise to images with Matlab program and noise density in salt & pepper is 0.05, the balloon snake is more insensitive to initial contour locations than the methods do not have pressure forces like the distance snake and GVF snake. This is due to the shape and edge strength of the desired boundary.

Distance snake required a bigger initial contour (e.g., double and triple the initial contour radius) than others in order to catch the attraction forces from the edge points in all directions.

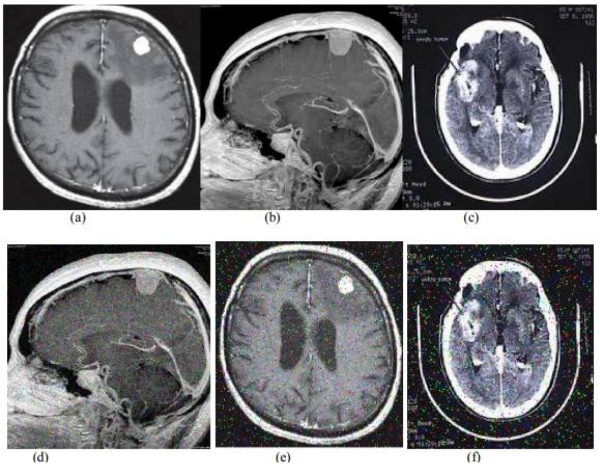

Figure 1: (a),(b),(c) Brain tumor (c),(d),(e) images with noise

The energy functional is defined as follows:

$$E_{snake} = \int_0^1 E_{snake}(v(s))ds \qquad (1)$$

$$E_{snake} = \int_0^1 E_{int}(v(s)) + E_{ext}(v(s))ds \qquad (2)$$

$$E_{ext} = E_{image}(v(s)) + E_{con}(v(s)) \qquad (3)$$

$$E_{snake} = \int_0^1 E_{int}(v(s)) + E_{image}(v(s)) + E_{con}(v(s))ds \qquad (4)$$

Where Eint , E ext , E image and E con respectively denote internal energy, external energy, external image energy and external constraint energy [3]. The internal energy, E int, is calculated based on the shape and location of the snake and serves to preserve the continuity and smoothness of the snake. The external energy term, E ext, is composed of two terms: the external image energy term and the external constraint energy term. The external image energy, E image , is calculated using image information, typically the negative magnitude of the gradient of the image, and is used to drive the snake towards image features like lines, edge and subjective contours.

The external constraint energy, E con, is an optional term that is responsible for forcing the snake away or towards any particular feature in the image. This optional term is defined by a user or some other higher level process. The expanded general form of the energy functional without the optional constraint energy term is:

$$E_{snake} = \int_0^1 \frac{1}{2}\alpha(s)\left|\frac{dv}{ds}\right|^2 + \frac{1}{2}\beta(s)\left|\frac{d^2v}{ds^2}\right|^2 + E_{ext}(v(s))ds \qquad (5)$$

Where α(s) and β(s) are non-negative weighting parameters that control the snake's tension (elasticity) and rigidity (inability to bend). In most applications and for this paper they are treated as constants. From calculus of variations, the snake that minimizes the energy functional must satisfy the following Euler equation:

$$-\frac{\partial}{\partial s}\left(\alpha(s)\frac{\partial v(s)}{\partial s}\right) + \frac{\partial^2}{\partial s^2}\left(\beta(s)\frac{\partial^2 v(s)}{\partial s^2}\right) + \nabla E_{ext} = 0 \qquad (6)$$

In compact form:

$$\alpha(s)v''(s) - \beta(s)v''''(s) - \nabla E_{ext} = 0 \qquad (7)$$

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The above equation can be viewed as a force balance equation:

$$F_{int} + F_{ext} = 0 \quad (8)$$

DISCUSSION

The internal force discourages stretching and bending while the external force pulls the snake towards the desired image edges. Using these force terms, the deformation process of the snake can be viewed as an interaction of forces.

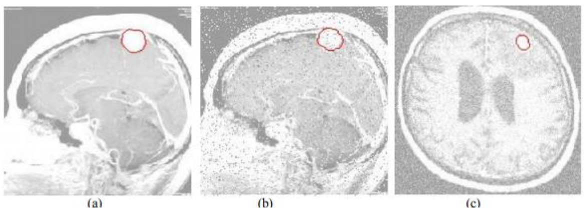

Fig.2(a) segmentation of original image with balloon snake (b), (c)balloon snake segmentation in image with salt &pepper and Gaussian noise

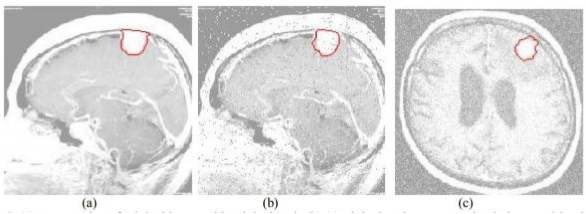

Fig. 3. (a)segmentation of original image with original snake(b),(c)original snake segmentation in image with salt & pepper and Gaussian noise

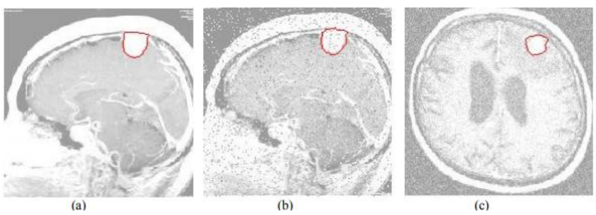

Fig. 4(a) segmentation of original image with distance snake (b), (c) distance snake segmentation in image with salt &pepper and Gaussian noise

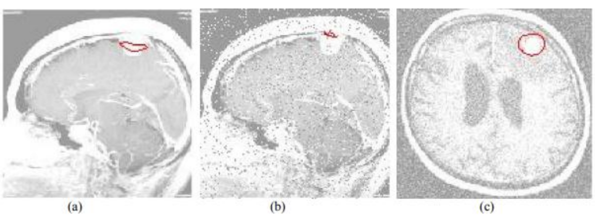

Fig. 5 (a) segmentation of original image with GVF snake (b), (c) GVF snake segmentation in image with salt & pepper and Gaussian noise

The method allowed for the inclusion of information from a good local edge detector. Internal pressure forces were introduced that allowed the snake to expand, allowing it to find the edges even when initialized within the Region of Interest (ROT). In addition to the above properties, the balloon force also allows the snake to pass through weak edges and actively seek the desired edge.

CONCLUSION

Image segmentation plays a central role in biomedical image processing. Tumor segmentation from MRI data is an important but time consuming task performed manually by medical experts. Automating this process is challenging due to the high diversity in appearance of tumor tissue, among different patients and in many cases, similarity between tumor and normal tissue. Parametric active contour method is one of many segmentation approaches.

REFERENCES

1. Azian Azamimi Abdullah, Bu Sze Chize and Yoshifumi Nishio (2012). “Implementation of An Improved Cellular Neural Network Algorithm For Brain Tumor Detection,” International Conference on Biomedical Engineering (ICoBE) , Penang, pp. 27-28.

2. Yu-Hsiang Wang, Tutorial: Image Segmentation.

3. Ishita Maiti, Dr. Monisha Chakraborty (2012). “A New Method for Brain Tumor Segmentation Based on Watershed and Edge Detection Algorithms in HSV Color Model, ” National Conference on Computing and Communication Systems (NCCCS), Vol. 73, No. 3, pp. 329–345.

4. J.Vijay, J.Subhashini (2013). “An Efficient Brain Tumor Detection Methodology Using K-Means Clustering Algorithm,” IEEE International conference on Communication and Signal Processing, pp. 653-657.

5. Bilotta E., Cerasa A., Pietro P., Quattrone A., Staino A., Stramandinoli F. (2010). “A CNN Based Algorithm for the Automated Segmentation of Multiple Sclerosis Lesions,” Evo Applications, Part I, pp. 211-220.

6. K. S. Angel Viji, J. Jayakumari (2012). “Performance evaluation of standard image segmentation methods and clustering algorithms for segmentation of MRI brain tumour images,” European Journal of

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Scientific Research, Vol.79, No.2, pp.166-179.

7. Laxman Singh, R. B. Dubey, Z. A. Jaffery, Zaheeruddin (2013). "Segmentation and characterization of brain tumor from MR images," IEEE International Conference on Advances in Recent Technologies in Communication and Computing.

8. Arash Azim Zadeh Irani and Bahari Belaton (2014). "A K-means Based Generic Segmentation System" Sixth International Conference on Computer Graphics, Imaging and Visualization.

9. Amitava Halder, Chandan Giri and Amiya Halder, Brain Tumor Detection using Segmentation based Object Labeling Algorithm.

10. K. S. Tamilselvan, Dr. G. Murugesan and B. Gnanasekaran (2013). "Brain Tumor Detection from Clinical CT and MRI Images using WT-FCM Algorithm," IEEE International Conference on Green Computing, Communication and Conservation of Energy (ICGCE), pp. 260-263.

11. Anam Mustaqeem, Ali Javed, Tehseen Fatima (2012). "An Efficient Brain Tumor Detection Algorithm Using Watershed & Thresh Holding Based Segmentation," International Journal of Image, Graphics and Signal Processing, Vol. 10, pp. 34-39.

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