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ACTIVE CONTOUR BASED LIVER IMAGE ANALYSIS

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ABSTRACT

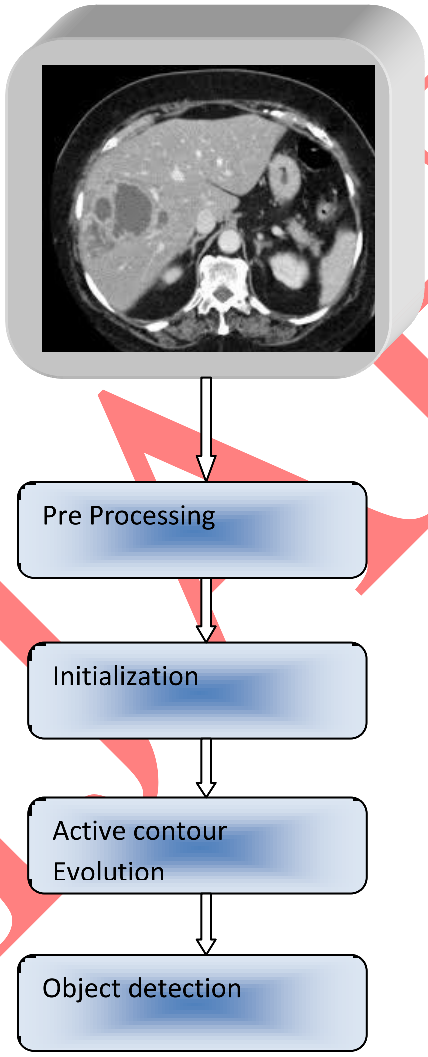
Accurate and fast image segmentation algorithm is of paramount importance for a wide range of medical imaging applications. The most widely used image segmentation algorithms are region based and typically rely on the homogeneity of the image intensities in the regions of interest, which often fail to provide accurate segmentation results. This paper addresses the application of active contours for robust tracking of contours. In this method motion estimation is embedded in the energy minimization process of the contours. This is possible using a dynamic programming approach for this minimization problem. This method has been successfully applied to the analysis of liver images.

INTRODUCTION

Liver and liver tumour segmentation on CT images is a challenging task due to the similarities in intensities of liver tissues with their surrounding organs. Also, the location of liver tumour is not exact in all cases which make the atlas based algorithm meaningless. These challenges must be considered while segmenting [1 2 3] liver and liver tumour. Thus, segmentation remains a challenging task in medical imaging field. The most common medical imaging techniques include Ultrasonagraphy (US), Computed Tomography (CT), and Magnetic Resonance Imaging (MRI). CT is often the preferred method for diagnosing many cancers to confirm the presence and size of tumors. By examining the CT image, the radiologist can plan and decide the proper treatment. Tracking of contours[4 5 6] has many applications in medical image processing. In image processing active contours embed them into a time dependent function. From this method we can improve the segmentation of image thereby increasing the detection of tumor effectively. A variety of algorithms have been proposed to solve the image segmentation problems. Among them active contour based methods[7 8 9 10] have wider range of uses, due to its high accuracy. The active contours[1,2] are defined by a continuous curve, closed or not. This curve will be evolved from one initial position to converge to the contour of interest. The process of evolution moves the position of the curve and which is deformed. Deform of curve from initial position situated near the object of interest is controlled by a function of its energy and the minimum position is reached when the contour is of interest. The technique of active contour has grown to the curve evolution theory, edge based models and then to region-based models. The idea of active contour model is to evolve a curve and is subjected to constraints. The curve moves downwards its interior normal and stops at the boundary of the objects. The most widely studied mathematical models in image processing is the active contour model, which is about the variational problem of minimizing a energy[11] functional involving a piecewise smooth representation of an image

This paper is organized as follows. In section II Block schematic is explained. Active contours are explained in Section III.Section IV presents the implementation of active contours. Energy optimization technique is presented in Section V.The results are discussed in Section VI.

BLOCK SCHEMATIC



FUNDAMENTALS OF ACTIVE CONTOURS

The parametric representation of a active contour is represented by the following notations

$C = \{v(s,t), y(s,t) \| s \in [a,b], t \in [0,T]\}$ where a, b denote the extremities (fixed, mobile, combined or not) of contour denoted the time variable and v(s, t) denoted the current point. To simplify writing, we will be using the notation v(s) instead of v (s, t).

The energy of the active contour [12 13]model comprises an internal energy term for regularization and an external energy term or fitness data, in which, the constraints of energy term can be added. This energy includes the intrinsic characteristics of the curve, the image features in the vicinity of the cure and the interaction between the curve and the image.

$$E(C) = E_{\text{int}}(C) + E_{ext}(C) + E_{image}(C) \qquad (1)$$

$$E(v(s)) = E_{\text{int}}(v(s)) + E_{ext}(v(s)) + E_{image}(v(s)) \qquad (2)$$

A. Internal energy

The internal energy of active contour regulates the contour, controls the intrinsic characteristics of the contour, manages and maintains cohesion points and the steepness of the curve. It's better to reduce the presence of oscillations and allow mitigating he effects of noise.

According to Tikhonov, $E_{\text{int}}(C)$ is introduced by expression:

$$E_{\text{int}}(v(s)) = \sum_{r=0}^{p} \int_a^b \left(\alpha_r(s) \left| \frac{\partial^r v(s)}{\partial s^r} \right|^2 \right) ds \qquad (3)$$

Where p is the order of the stabilizer and $\alpha_r(s)$ the coefficient balances that can be interpreted in terms of physical characteristics curve (continuity, stiffness, elasticity...)

The internal energy selected by Kass. et al , is limited to the case p=2 and becomes:

$$E_{\text{int}}(v(s)) = \int_a^b \left(\alpha(s) \left| \frac{\partial v(s)}{\partial s} \right|^2 \right) ds + \int_a^b \left(\beta(s) \left| \frac{\partial^2 v(s)}{\partial s^2} \right|^2 \right) ds \qquad (4)$$

The first order term is the first derivative of v with respect to s and corresponds to the tension (as a thin membrane behaviour). It takes a large value when the curve is weakening. It is controlled by coefficient α(s), where α(s) is equal to zero curve can present discontinuities. So, we also call the energy continuity.

The second term is the second order derivative of v with respect to s and corresponds to the curve or the elasticity (a thin plate like behaviour). It takes an important value when the curve quickly curves that is the corners. It is controlled by coefficient β(s). When β(s) is equal to zero the curve can take a strong convexity, when β(s) is large, the curve will tend to a circle if it is closed or straight if it is open.

B. External Energy

The external energy is the external constraints to define the relation with the application that promote a specific type of deformation. The external energy used to introduce, via intermediate of the user, the high-level information. This is reflected by the presence of repulsion forces at certain points of the curve or by the presence of forces simulating elastic elongation of a spring between two points of the curve. The high level information can be associated with the presence of beforehand detected boundaries or constraints or control points. In certain notations, energy image is contained in the external energy or it can be contained in an external force.

C. Image energy

The energy picture defines the interaction with the object image segmentation, it can be a force of repulsion or attraction force and the two forces offset each other. It involves the image features that are seeking to develop. In the case where one seeks to highlight areas of high contrast, we can select an image energy given by the relation of the gradient or intensity.

To research areas of high contrast in the image, we use the function follows:

$$E_{image}\left(v\left(s\right)\right)=-\int_{a}^{b}\left|\nabla^{*}I\left(v\left(s\right)\right)\right|^{2}ds \qquad (5)$$

Where $\nabla^{*}I\left(v\left(s\right)\right)$ represents the gradient of picture I in the vicinity of the curve v(s).In the case In the case the points of contours are defined as the maximum gradient of formulation is used:

$$E_{image}\left(v\left(s\right)\right)=-\int_{a}^{b}\left|\nabla\left(g_{\sigma}*Iv\left(s\right)\right)\right|^{2}ds \qquad (6)$$

where ∇ is the gradient of image and g_{σ} is Gaussian centred standard deviation σ. A minimum energy will be achieved if the curve passes through the points of maximum gradient of the smoothed image by Gaussian filter.

- Intensity

The energy selects the dark or light areas depending on the selected sign.

$$E_{image}\left(v\left(s\right)\right)=\pm\int_{a}^{b}\left(I\left(v\left(s\right)-i_{0}\right)^{2}ds \qquad (7)$$

The value i_0 is a certain threshold. It can thus favour the position of the contour in a given area.

IMPLEMENTATION

The dynamic programming is one of the classical methods for the resolution of the optimization problems. This technique makes it possible to track the objects with large motion and deformation without increasing the time complexity. The energy equation used is

$$E_i\left(v_{i+1}, v_i\right) = \min_{v_{i-1}}\left\{E_{i-1}\left(v_i, v_{i-1}\right) + \alpha\left|v_i - v_{i-1}\right|^2 + \beta\left|v_{i-1} - 2v_i + v_{i+1}\right|^2 + E_{image}(v_i)\right\} \quad (8)$$

RESULTS and DISCUSSION

CT scan is good non-invasive tool and can be used as first live imaging modality for differentiating benign and malignant focal liver lesions.CT is a standardized procedure for the detection and characterization of a large variety of benign and malignant liver lesions. The proposed functions are computed from an arbitrary region **Ω** in the image domain Ωo. If the region of interest can be roughly and automatically obtained in some way, such as thresholding, and then we can use these roughly obtained regions as the region **Ω**. According to the evolution of equations the parametric curves converged to the region of interest. The liver extraction scheme developed in this work can be used as a first and necessary step in computer-aided diagnosis for the detection of liver tumors in hepatic CT. The algorithm was tested on two sets of benign and malignant liver tumor CT images. Our computerized scheme provides an efficient and accurate way of segmenting liver tumors in CT images; thus, it would be useful for radiologists in their analysis of CT liver images. We first show the results for two sets of Benign liver tumor CT images by segmenting the liver and tumor using active contours as in fig.2 (a), fig.3 (a) and Malignant liver tumor images in fig.4 (a), fig.5 (a). Liver with benign tumour are separated fig.2 (b) and fig 3(b) respectively. Tumour alone is separated in fig.2(c) and fig 3(c) respectively. Liver with malignant tumor are separated in fig .4(b) and fig .5(b) respectively. Tumour alone is separated in fig.4(c) and fig 5(c).In fig.2(b) the region of interest is clearly visible and in fig.2(c) the tumour is extracted and is approximate circular in shape ,can be used for further analysis. In fig.3 (b) the region of interest is extracted and in fig.3(c) the tumour is extracted and is approximate elliptical in shape, can be used for further analysis. In fig.4 (b) liver with tumour is clearly visible and in fig.4(c) the tumour is extracted and is non geometric in shape. In fig.5 (b) the region of interest is clearly visible and in fig.5(c) the tumour is extracted and is non geometric in shape, can be used for further analysis.

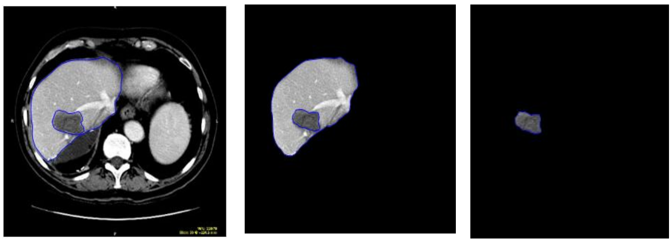


Fig.2(a) Fig.2(b) Fig.2(c)

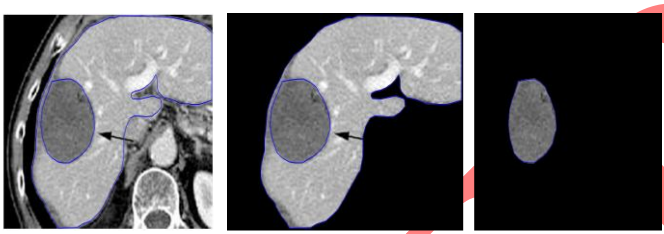


Fig.3 (a) Fig.3 (b) Fig.3(c)

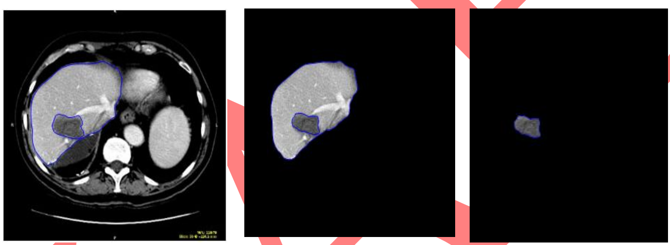


Fig.4 (a) Fig.4 (b) Fig.4(c)

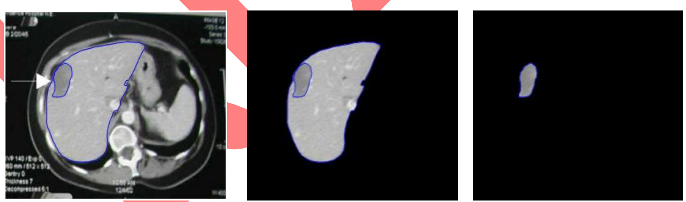


Fig.5 (a) Fig.5 (b) Fig.5(c)

CONCLUSION

Abdomen CT images are used in the investigation. Active contour based image operations is used to obtain the exact location of the tumor.The robustness of the system can be used to detect the liver tumor at the early stages and hence save lives.

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