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Liver segmentation with new supervised method to create initial curve for active contour

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ABSTRACT

The liver performs a critical task in the human body; therefore, detecting liver diseases and preparing a robust plan for treating them are both crucial. Liver diseases kill nearly 25,000 Americans every year. A variety of image segmentation methods are available to determine the liver's position and to detect possible liver tumors. Among these is the Active Contour Model (ACM), a framework which has proven very sensitive to initial contour delineation and control parameters. In the proposed method based on image energy, we attempted to obtain an initial segmentation close to the liver's boundary, and then implemented an ACM to improve the initial segmentation. The ACM used in this work incorporates gradient vector flow (GVF) and balloon energy in order to overcome ACM limitations, such as local minima entrapment and initial contour dependency. Additionally, in order to adjust active contour control parameters, we applied a genetic algorithm to produce a proper parameter set close to the optimal solution. The pre-processing method has a better ability to segment the liver tissue during a short time with respect to other mentioned methods in this paper. The proposed method was performed using Sliver CT image datasets. The results show high accuracy, precision, sensitivity, specificity and low overlap error, MSD and runtime with few ACM iterations.

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1. Introduction

Each year, approximately 25,000 Americans die from liver diseases such as liver cancer. Cancer is typically caused by the irregular and unmanageable growth of cells [1]. Surgery and tumor removal are the standard method for curing liver cancer; however, before these can occur, the disease must be diagnosed and the tumor must be located. Diagnostic approaches can be divided into two categories: invasive processes, such as needle biopsy (which are not recommended) [2], and noninvasive processes, such as medical imaging techniques, including computed tomography (CT), ultrasonography (US), and magnetic resonance imaging (MRI) [3]. When clinical experts work with medical representations like CT images, they need to extract liver tissue from other organs. A physician can segment the liver area manually or by using computer aided methods involving semi-automatic or automatic segmentation processes. Liver segmentation is one of the most challenging and difficult processes [4] because of its proximity to adjacent organs, the similarity in the intensity and textures of those organs to the liver, and the possible blurring of common boundaries. Many segmentation methods have been introduced for image segmentation, such as Region Growing model [5], Level Set model [6], Active Contour Model (ACM) [7–11], Fuzzy-based methods like Fuzzy C-Means [12–14], and Graph Cut model [15–19]. But no one model is exhaustive to successfully extract the desired region from different medical images belonging to a variety of patients. Also each one has some shortages for example Region Growing, Level Set and Active Contour models need to determine initial region, FCM takes long time for segmentation and graph cut needs training dataset.

This study focuses on improving the ACM. Initially presented by Kass in 1988 [20], Active Contour is a 2D curve that moves consistent with the minimization of an energy function, and surrounds a target object in the specified image. The advantage of the ACM is its provision of a smooth and closed curve; however, its performance is dependent on accurately delineating the initial curve points [21]. The initial curve must be adequately proximate to the specified object boundaries [22]; otherwise, the contour may lead to local minima entrapment. To solve local minima entrapment, Cohen [23] proposed a new balloon force that equips contours with the ability to expand or contract, making the curve more dynamic [24]; and Xu and Prince [25] introduced gradient vector flow (GVF), wherein a GVF snake does not need to define an initial curve to capture a specified object, and can converge to concave and convex boundaries [26]. Also, there are other works to overcome local minima entrapment that can be found in [27–29]. Our pre-processing method creates initial curve close to the desired region boundaries during a short time so that the ACM needs few iterations, but GVF and Balloon energy are incorporated in the ACM because of more adaptability to the ACM to help better initial curve refinement. Foruzan et al. [30] used prior knowledge about the structure and location of the liver to solve ACM's initial curve problem in liver segmentation, while Mei and Xu [31] proposed another way to produce an initial curve based on shape sharing phenomenon Furthermore, Bakir et al. [22] incorporated the divergence of vector flow and the Dijkstra algorithm to determine the initial curve for the Active Contour Model; and Lan and Min [32] used marker control watershed to initialize the Active Contour Model.

Additional studies providing initial segmentation for ACM based on region growing [33], FCM [34,35], Markov random field [36] and Ant Colony Algorithm [37] have also been conducted.

An added challenge of the ACM is proper parameter setting. To overcome this problem, Talebi and Ayatollahi [38] and Rousselle et al. [39] produced optimum parameters for the Active Contour Model by using the genetic algorithm. Further research [40,41] has also been conducted regarding ACM optimization utilizing the genetic algorithm.

Our proposed method, based on image energy according to Kass's formulation [20], extracts liver tissue from other organs in abdominal images and provides the initial curve for ACM. Then, the process of thresholding image energy and performing morphological filters creates an initial segmented region which will ultimately be refined by ACM. When segmentation results are undesirable, the user can change or adjust threshold amplitudes as needed.

In order to optimize active contour parameters, we perform genetic algorithm before running ACM. The parameters are then fixed until the ACM is executed across all images, each ACM execution containing ten iterations.

In the following text, the second section outlines our materials of work; the third section introduces our proposed method; the following section contains experimental results and discussion and compares our method with those of Sandhu et al. [42], Yuan et al. [43], Balla-Arabe et al. [44], Li et al. [45], Bresson et al. [28], Huynh et al. [46] and Heimann et al. [47] and the paper closes with our conclusion.

2. Materials

2.1. Classic active contour

The 2D classic active contour is presented as follows:

$$C(s) = (x(s), y(s)) \tag{1}$$

where $x(s)$ and $y(s)$ are coordinate points on image $I(x,y)$. The energy function of the curve is:

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

E_{int} controls the smoothness and continuity of curve, and E_{ext} attracts the contour to the desired features [11].

$$E_{int} = \frac{1}{2}\left(\alpha|C'(s)|^2 + \beta|C''(s)|^2\right) \tag{3}$$

The first term is related to the elasticity of the curve, and α is a coefficient which controls it. The second term is related to strength and resistance against sudden change, which is controlled by the β coefficient [38]. In other words, α and β, respectively, control the continuity and curvature of the contour.

$$E_{ext} = E_{con} + E_{image} \tag{4}$$

E_{con} is the external constraint force, and E_{image} is the image force. E_{image} can be written as follows:

$$E_{image} = w_{line}E_{line} + w_{edge}E_{edge} + w_{term}E_{term} \tag{5}$$