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Combined endeavor of Neutrosophic Set and Chan-Vese model to extract accurate liver image from CT scan

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ABSTRACT

Many different diseases can occur in the liver, including infections such as hepatitis, cirrhosis, cancer and over effect of medication or toxins. The foremost stage for computer-aided diagnosis of liver is the identification of liver region. Liver segmentation algorithms extract liver image from scan images which helps in virtual surgery simulation, speedup the diagnosis, accurate investigation and surgery planning. The existing liver segmentation algorithms try to extort exact liver image from abdominal Computed Tomography (CT) scan images. It is an open problem because of ambiguous boundaries, large variation in intensity distribution, variability of liver geometry from patient to patient and presence of noise. A novel approach is proposed to meet challenges in extracting the exact liver image from abdominal CT scan images. The proposed approach consists of three phases: (1) Pre-processing (2) CT scan image transformation to Neutrosophic Set (NS) and (3) Post-processing. In pre-processing, the noise is removed by median filter. The "new structure" is designed to transform a CT scan image into neutrosophic domain which is expressed using three membership subset: True subset (T), False subset (F) and Indeterminacy subset (I). This transform approximately extracts the liver image structure. In post processing phase, morphological operation is performed on indeterminacy subset (I) and apply Chan-Vese (C-V) model with detection of initial contour within liver without user intervention. This resulted in liver boundary identification with high accuracy. Experiments show that, the proposed method is effective, robust and comparable with existing algorithm for liver segmentation of CT scan images.

1. Introduction

The liver is a vital organ that has many roles in the body, including building proteins and blood clotting factors, manufacturing triglycerides and cholesterol, glycogen synthesis and bile production. The liver is the largest internal organ. Infections such as hepatitis, cirrhosis (scarring), cancer and over effect of medications are identified diseases within liver. The foremost stage for computer-aided diagnosis of liver is the identification of liver region. Liver segmentation algorithms extract liver image from scan images which helps in virtual surgery simulation, speedup the disease diagnosis, accurate investigation and surgery planning.

The liver segmentation from CT scan images has gained a lot of importance in medical image processing field because 1 in every 94 men and 1 in every 212 women born are susceptible to liver cancer in their life time [1,2]. Liver cancer is one of the most common diseases, with increasing morbidity and high mortality [3,4]. The Liver cancer treatment requires maximum radiation dose to the tumour and minimum toxicity to the surrounding healthy tissues. This is the major challenge in clinical practice [5,6]. Selective Internal Radiation Therapy (SIRT) with Yttrium-90 (Y-90) microspheres is an effective technique for liver-directed therapy [7]. SIRT dosimetry requires accurate determination of the relative functional tumour(s) volume(s) with respect to the anatomical volumes of the liver in order to estimate the necessary Y-90 microsphere dose [8,9]. Clinically, accurate liver volume determination is accomplished through tedious manual segmentation of the entire Computerized Tomography (CT) scan. A task is greatly dependent on the skill of the operator. Manual segmentation is time consuming. Thus many automatic or semiautomatic techniques are available for segmentation and determine the volume of the liver accurately. This facilitates the operational process from a physician's viewpoint.

Extracting liver from CT scan or MRI scan images is of prime importance. Considerable work has been done in extracting liver from CT scan or MRI scan images; so a general solution has remained as challenge. Failure in getting a reliable and accurate segmentation algorithm is due to (1) Neighbour organs of liver like

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kidneys, heart, stomach, etc. have same intensity level. (2) There is no definite shape, weight, size, volume or texture for a liver. All these parameters are subjective. (3) Edges are weak (4) Presence of artifacts in MRI images or CT scan images. (5) Variability of liver geometry from patient to patient. (6) Large variation in pixel level range throughout the liver section as well as from patient to patient.

2. Related work

Chen et al. [10] designed Chan-Vese model for liver segmentation in which Gaussian function is used to find liver likelihood image from CT scan images and obtaining the liver boundary using Chan-Vese model. They have used morphological operation to improve the results. Song et al. [11] proposed an automatic liver boundary marking method which is based on an adaptive Fast Marching Method (FMM). The liver image is separated from CT scan by manually fixing pixel intensity between 50 and 200. Median filter is applied to reduce noise and liver image is enhanced by sigmoidal function. In this, the image is converted into binary and FMM is applied to find liver boundary accurately. Wu et al. [4] developed a novel method for automatic delineation of liver on CT volume images using supervoxel-based graph cuts. This method integrates histogram-based adaptive thresholding, Simple Linear Iterative Clustering (SLIC) and graph cuts algorithm. Mehrdad et al. [12] proposed random walker based framework. In this, liver dome is automatically detected based on location of the right lung lobe and rib caged area and liver is extracted utilising random walker method. Xiaowei et al. [13] introduced a multi-atlas segmentation approach with local decision fusion for fast automated liver (with/without abnormality) segmentation on Computational Tomography Angiography (CTA). Zheng et al. [14] designed a feature-learning-based random walk method for liver segmentation using CT images. Four texture features are extracted and then classified to determine the probability corresponding to the test images. In this, seed points on the original test image are automatically selected. Peng et al. [15] designed a novel multiregion-appearance based approach with graph cuts to delineate the liver surface and a geodesic distance based appearance selection scheme is introduced to utilize proper appearance constraint for each subregion. Platero et al. [16] proposed a new approach to segment liver from CT scan which is combination of low-level operations, an affine probabilistic atlas and a multiatlas-based segmentation. AlShaikhli et al. [17] presented a novel fully automatic algorithm for 3D liver segmentation in clinical 3D CT images based on Mahalanobis distance cost function using an active shape model implemented on MICCAI-SLiver07 achieving in an accurate results. Li et al. [18] developed liver segmentation using 3D-convolutional neural network and accuracy of initial segmentation is increased with graph cut algorithm and the previously learned probability map. Li et al. [19] developed a technique to detect the liver surface which includes construction of statistical shape model using the principal component analysis; Euclidean distance transformation is used to obtain a coarse position in a source image. And accurate detection of the liver is obtained using deformable graph cut method. Zheng et al. [20] designed a tree-like multiphase level set algorithm for segmentation, based on the Chan-Vese model to detect objects in an image. The algorithm is effective for images which have sub-objects in the region.

3. Neutrosophic Set (NS)

Neutrosophic Set (NS) was introduced by Smarandache [21]. In neutrosophic set theory, every event has not only a certain degree of the truth but also a falsity degree with indeterminacy. These parameters are considered independently from each other [21,22]. An entity {S} is considered with opposite {Anti-S} and neutrality {Neut-S}. The {Neut-S} and {Anti-S} are referred to as {Non-S} [22].

To apply the concept of NS to image processing, the image should be transformed into the neutrosophic domain. Image P of size X^*Y with K grey levels can be defined as three arrays of neutrosophic images described by three membership sets: T (true subset), I (indeterminate subset) and F(false subset). Therefore, a pixel $P(i,\ j)$ in the image transferred into the neutrosophic domain can be represented by $P_{NS}=\{T(i,\ j),\ I(i,\ j),\ F(i,\ j)\}$ or $P_{NS}=P(t,\ i,\ f)$. It means that the pixel is $\%\,t$ true, $\%\,i$ indeterminate and $\%\,f$ false. Here, t varies in T (white pixel set), i varies in I (noise pixel set) and f varies in F (black pixel set) which are defined as follows [21–24].

$$T(i,j) = \frac{\bar{G}(i,j) - \bar{G}_{min}}{\bar{G}_{max} - \bar{G}_{min}} \tag{1}$$

$$I(i,j) = \frac{d(i,j) - d_{min}}{d_{max} - d_{min}} \tag{2}$$

$$F(i,j) = 1 - T(i,j) \tag{3}$$

Where $\bar{G}(i,j)$ is local mean value of the pixel of the window and given by following equation

$$\bar{G}(i,j) = \frac{1}{w*w}\sum_{m=i-w/2}^{m=i+w/2}\ \sum_{n=i-w/2}^{j+w/2} G(m,n) \tag{4}$$

$d(i,\ j)$ is absolute value of the difference between intensity $G(i,\ j)$ and its local mean value $\bar{G}(i,j)$ and given as

$$d(i,j) = abs(G(i,j) - \bar{G}(i,j)) \tag{5}$$

$G(i,\ j)$ is intensity value of the pixel $P(i,\ j)$, w is size of sliding window, $\bar{G}_{min}$ and $\bar{G}_{max}$ are minimum and maximum of the local mean values of the image, respectively, d_{min} and d_{max} are minimum and maximum value of $d(i,\ j)$ in whole image.

4. Basic Chan-Vese model

All the classical snakes and active contour model depends on the image gradient to stop curve evolution, so these models can detect only objects with edges defined by gradient [25]. In biomedical images, edges are fragile and image is noisy. Hence stopping function is never zero on edges and the curve evolution may pass through the boundary. T.F. Chan and L.A. Vese have designed a new active contour model for image segmentation based on region instead of gradient, which is called Chan-Vese[C-V] model [26]. In this section, summary of original C-V approach [25] is presented for reader convenience.

Let $I(x)$ be the brightness function of input image. The image is defined over a two-dimensional area, denoted by $\Re$. It is assumed that, the image contains objects and background which have constant brightness, denoted by B_o and B_b respectively. Let C represents closed curve in the image that separates the objects and background. In C-V model [26], the following energy function is minimised.

$$\begin{aligned} f(B_o,B_b,C) = {} & \mu\cdot Length(C) + \lambda\cdot Area(inside(C)) \\ & +\lambda_o\int_{insideC}(I(x)-B_o)^2dx \\ & +\lambda_b\int_{outsideC}(I(x)-B_b)^2dx \end{aligned} \tag{6}$$

Where λ_o,λ_b,μ, λ are parameters with suitably chosen values and are greater than or equal to zero. Eq. (6) can be minimised by taking function $\phi(x)$,$x\in\Re$, takes a value of greater than 0 inside the object, less than 0 outside the object and equal to zero on