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The domain knowledge based graph-cut model for liver CT segmentation

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ABSTRACT

In this paper, we present a semi-supervised approach for liver segmentation from computed tomography (CT) scans, which is based on the graph cut model integrated with domain knowledge. Firstly, some hard constraints are obtained according to the knowledge of liver characteristic appearance and anatomical location. Secondly, the energy function is constructed via knowledge based similarity measure. A path-based spatial connectivity measure is applied for robust regional properties. Finally, the image is interpreted as a graph, afterwards the segmentation problem is casted as an optimal cut on it, which can be computed through the existing max-flow algorithm. The model is evaluated on MICCAI 2007 liver segmentation challenge datasets and some other CT volumes from the hospital. The experimental results show its effectiveness and efficiency.

1. Introduction

As a noninvasive and painless medical test, abdominal CT scan has been widely used in hospitals of China for liver cancer diagnosis [1]. The first and fundamental step in computer aided diagnosis is the liver segmentation, which is of benefit in many aspects for further treatment, such as three-dimensional visualization, quantitative analysis, and surgery planning.

Nevertheless, the topic is still an arduous task for the following reasons. Firstly, the CT images are often very noisy that inevitably exist ambiguous boundaries between the liver and its adjacent organs, including abdominal wall, right kidney, heart, stomach and gallbladder. Sometimes, it becomes even worse that the boundaries disappeared because of the poor imaging quality. Secondly, the liver presents significant inter-patient and intra-patient anatomical variations, which make it difficult to generate a uniform benchmark. Thirdly, the liver has diversity problem on intensity distributions, i.e., the bright vessel, the regular healthy tissue and the dim tumor. Consequently, the intensity based algorithms always lack in accurate segmentation results. Finally, the slice-by-slice segmentation approach is time consuming, and the results on each slice are independent of each other. Therefore, a more efficient and accurate volume segmentation method is needed.

Given the difficulty of liver segmentation, many models have been proposed with varying degrees of success [2]. However, some critical problems remain unsolved. Most existing shape model based methods focus on the representation of the liver shape [3–5], yet they fall short of accurately segmenting the liver because of the large shape variability among different patients. Moreover, the results are highly dependent on initialization. Although in [6] a hierarchical shape was represented with a really fast processing speed, the model suffered from seriously blurred boundaries between liver and vicinity organs. For coping with shape variation problems in segmentation, a sparse information model was exploited in [7], but little information has been provided on the model efficiency. Moreover, the results relied too much on the data volumes used to build the sparse model.

In recent years, the most popular used models are in terms of energy minimization [8], among which the level set based method and graph based method are overwhelming adopted. In the context of liver segmentation, the level set based method always generates local minima of the energy function, be sensitive to contour initialization and has large iterative computation burden [9,10]. Especially in dealing with tumors located near the liver surface, the segmentation result often tends to eliminate them from the target since the local optimization. Meanwhile, the vessels also need to be additionally segmented and remerged into the final result. Combining the two popular methods, a graph cuts based active contours approach was presented in [11], which used graph cuts to iteratively deform the contour. It failed to jump over local minima in spite of leading a more global and smooth result. Meanwhile, the initial contour should be strictly set around the target exterior border, otherwise yielded a terrible segmentation result. The graph cut models demonstrate a great potential with the advantage of global optima and practical efficiency [12]. When it comes to liver segmentation [13,14], sometimes the standard graph cut model

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is incapable under the circumstance of seriously blurred boundaries and similar intensities between the liver and its neighbor organs. What is more, the model is sensible to the energy function parameters which are only from interactive information or empirical estimation. To address the robustness issue, we extend the graph cut model with domain knowledge information in the form of initialization and similarity constraints. The commonly used knowledge in description of liver CT images involves appearance feature, anatomical location and spatial connectivity [15]. Our main contribution is devising a knowledge based energy function that is minimized under a given set of region and boundary conditions.

The paper is organized as follows. A problem formulation for liver CT image segmentation is provided in Section 2. The proposed domain knowledge based graph-cut model for liver CT segmentation is elaborated in Section 3. In Section 4, the experimental results together with performance evaluation of the proposed model are presented and discussed. Section 5 concludes the paper.

2. Problem formulation

Let $P = \{1, 2, \ldots, M\}$ be the set of image voxels, $L = \{0, 1\}$ is the set of labels corresponding to the image background and the object to be segmented. The goal of image segmentation is to find an optimal labeling configuration f: $P \to L$ for each voxel in the image, where f is both piecewise smooth and consistent with the observed data. In this framework, the problem can be naturally formulated in terms of minimizing the following energy [16].

$$E(f) = E_{data}(f) + E_{smooth}(f) = \sum_{p \in P} D_p(f_p) + \sum_{(p,q) \in N} S_{p,q}(f_p, f_q). \qquad (1)$$

where data term D_p is a data penalty function indicates how well the label f_p fits the voxel p, smooth term $S_{p,q}$ is an interaction potential which encourages spatial coherence by penalizing discontinuities between neighboring voxels p and q, $N = \{N_i | \forall i \in P\}$ is the 6-connected neighborhood system in 3D space. The energy combines boundary regularization with regional properties, which provides a global optimal and robust solution for image segmentation.

Generally speaking, the statistics of a voxel in a medical image are related to the statistics of the voxels in a small local neighborhood around it [17], which means the label assigned to a voxel depends only on the labels assigned to its neighbors. This condition satisfies the Markovian property.

$$\Pr(f_i | \{f_j : j \in P - \{i\}\}) = \Pr(f_i | \{f_j : j \in N_i\}), \quad \forall i \in P. \qquad (2)$$

Assuming $F = \{F_1, F_2, \ldots, F_M\}$ as a field of random variables, each variable F_i is associated with a voxel $i \in P$ and takes a value from L, any possible assignment of labels $f = \{f_1, f_2, \ldots, f_M\}$ is essentially a realization of the field. The segmentation problem is formulated as maximum a posterior estimation of a Markov random field f that requires minimization of a posterior energy conditioned over the observed data X [16].

$$E(f|X) = \lambda \cdot \sum_{p \in P} -\log \Pr(x_p | f_p) + (1 - \lambda) \cdot \sum_{p \in P} \sum_{q \in N_p} K(p, q) \cdot \delta_{f_p \neq f_q}. \qquad (3)$$

where $\lambda > 0$ controls the balance between the two energy terms, $\Pr(x_p|f_p)$ is a likelihood function of data feature x_p associated with label f_p, N_p is the 6-connected neighbor set of p in 3D space, $K(p, q)$ is a positive penalty function, and δ is a two-valued indicator function with 1 only if $f_p \neq f_q$, otherwise $\delta = 0$.

3. Model description

3.1. Domain knowledge based initialization

In most cases, the CT images do not have sufficiently distinct regional properties that more necessary hard constraints should be incorporated into the global optimization framework [18]. In particular, this kind of hard constraints may come directly from the following domain knowledge, which focuses on the liver location, size and intensity distribution:

- The liver is located in the right upper quadrant of the abdominal cavity, resting just below the diaphragm. It lies to the right of the stomach and overlies the gallbladder, and surrounded by the right kidney, heart, rib and spine. It is connected to two large blood vessels, i.e., the hepatic artery and the portal vein.
- The liver is both the largest internal organ and gland in the human body, and sure the largest organ in the abdominal cavity.
- For liver cancer cases, the liver region consists of tumor tissues, healthy tissues and blood vessels, with intensity distribution approximately over the range of 20–90 HU (Hounsfield Units), 90–150 HU, and 150–250 HU. While the intensity of thoracic spine with ribs is about 300–600 HU.

In this paper, the hard constraints are either automatically or manually selected as seeds. Assuming that O and B denote the set of object and background seeds, they should satisfy: $O \cap B = \phi \,\&\, \forall p \in O : f_p = 1 \,\&\, \forall p \in B : f_p = 0$. It means the object seeds are labeled with 1 and the background seeds have the label of 0, meanwhile the two seed sets should not intersected at all. Automatically set seeds are initialized according to the third domain knowledge: all the voxels with intensities less than 0 HU or more than 300 HU are marked as part of B. On the other hand, manually controlled seeds are obtained by user interactive tools, such as bush and lasso strokes. For a more distinct representation, the object seeds in O are chosen respectively around the healthy tissues, blood vessels and tumor tissues, while the rest of background seeds in B are marked around the seriously ambiguous boundaries between liver and its neighbor organs.

In addition, since the resolution of CT scanners keeps increasing rapidly, it is not rare that a volume data has more than hundreds of millions voxels, while only about one-third of them belong to the region of interest (ROI). Therefore, the computing space can be restricted in the light of the first two domain knowledge. Further discussion with experimental results will be given in Section 4.1.

3.2. Energy formulation with domain knowledge

3.2.1. Construction of smooth term

The term $S_{p,q}$ is interpreted as a penalty for a discontinuity between neighbor voxels p and q, which is typically used to guarantee that the resulting segmentation has smooth boundaries.

In 3D space, q is only searching along the nearest 6-connected neighborhood of p in order to improve efficiency. The more similar p and q are, the larger cost of the penalty is. The penalty will decrease close to zero when the two neighbor voxels are very different. The similarity measure can be based on local intensity gradient, Laplacian zero-crossing, gradient direction, geometric and so on [18]. For most cases in liver segmentation, a Gaussian model based on intensities serves as a good choice for the smooth term, which can be expressed as follows:

$$K(p, q) = e^{-(I_p - I_q)^2 / 2\sigma^2} (q \in N_{p(6)}). \qquad (4)$$