Object information based interactive segmentation for fatty tissue extraction

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ABSTRACT

Lymph nodes are very important factors for diagnosing gastric cancer in clinical use, and are usually distributed within the fatty tissue around the stomach. When extracting fatty tissues whose structures and textures are complicated, automatic extraction is still a challenging task, while manual extraction is time-consuming. Consequently, semi-automatic extraction, which allows introducing interactive operations, appears to be more realistic. Currently, most interactive methods need to indicate the position and main features in both the object and background. However, it is easier for radiologists to only mark object information. Due to this issue, a new Object Information based Interactive Segmentation (OIIS) method is proposed in this paper. Different from the most existing methods, OIIS just needs to input the object information, while the background information is not required. Experimental results and comparative studies show that OIIS is effective for fatty tissue extraction.

1. Introduction

Gastric cancer has become the second leading cause of cancer death around the world. Lymph node metastasis is very important for prognosis in gastric cancer and radiologists hope to know the status of lymph nodes as much as possible [1–3]. According to the clinical domain knowledge, lymph nodes are usually distributed within the main fatty tissue which should be extracted accurately around the stomach.

As the structures and textures are complicated and fatty tissues vary from patient to patient, automatic extraction is still a challenging task. Manual extraction is time-consuming and frequently not applicable in clinical routine [4]. Consequently, it appears more realistic to develop methods enabling to interactively guide extracting process in clinical use [5]. Semi-automatic extraction methods (interactive segmentation) which introduce interactive information have been proposed [6–10] and have received more attentions recently. Compared to automatic methods, interactive segmentation can achieve more satisfactory results [11], which are utilized in this paper.

Currently, interactive segmentation has been applied to many medical tasks [12–14] and several methods have been proposed. In early methods, regional or boundary properties are utilized, such as active contour [8] and intelligent scissors [7]. Then several algorithms, which consider both regional and boundary properties,

are proposed, such as graph cut based methods [7–9] and the random walks algorithm [10]. Recently, region merging methods [15,16] become popular as they are more robust and need lower computational cost.
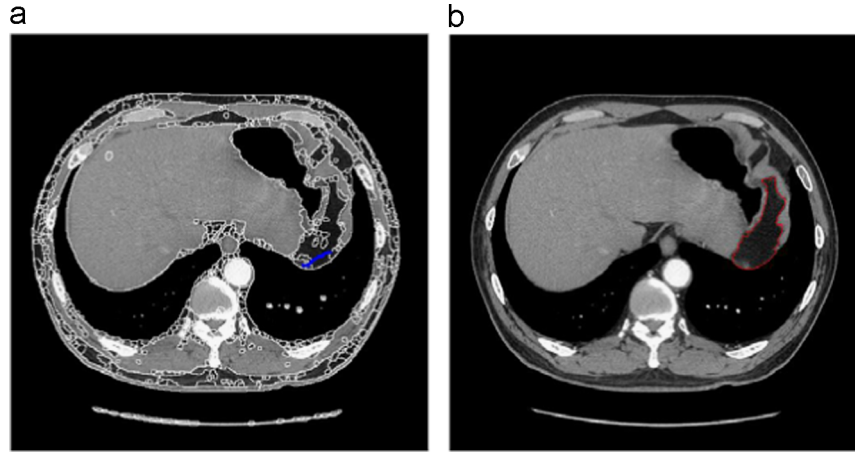
If the interactive information is introduced as markers, most current methods need to input markers to indicate the position and main features in both the object and the background areas. However, if radiologists just need to input object markers and do not need to input background markers, it is easier for them to use and not to care about so many organs and tissues in the background. Meanwhile, in clinical use, the less the user inputs, the more convenient and more robust the interactive algorithm is. An Object Information based Interactive Segmentation (OIIS) method is proposed in this paper. Different from the most existing methods, OIIS only needs to input markers on a small part of the fatty tissue, and background markers are not required. The image is divided into small regions by an over-segmentation method at first, radiologists then input the markers on fatty tissue and the contour can be extracted. In a word, OIIS is a simple yet effective method for fatty tissue extraction.

The rest of the paper is organized as follows. The proposed method for extracting fatty tissue is presented in Section 2. The experimental results and analysis are shown in Section 3. The paper is concluded in Section 4.

2. Proposed OIIS method

In this section, the initial segmentation and object marking are given at first. The region representation and similarity measure are

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Fig. 1. An example image. (a). The interactive information input by user (in blue) and the initial segmentation. (b) The extracting results marked red by OIIS. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

shown in the second subsection. Finally the fatty tissue extrication is described.

2.1. Initial segmentation and object marking

As OIIS is a region merging method, an initial segmentation is needed. There are various over-segmentation methods such as mean shift [17], watershed [18] and super-pixels [19]. As mean shift have less over segmentation and can keep the object boundaries well, it is chosen and the software named as EDISON system [20] is applied.

Interactive information such as lines, curves and strokes on an object can be input by users. The regions which have pixels inside the fatty tissue markers are called fatty tissue marker regions. Fig. 1(a) shows an example of the fatty tissue markers using simple blue lines and only a small portion of the fatty tissue regions are needed to mark. The whole scene consists of two parts: the marker fatty tissue regions and unmarked regions.

2.2. Region representation and similarity measure

To achieve the final extraction, some descriptors are needed, such as the grayscale intensity, edge, texture, and size of the region. Grayscale intensity histogram which is used in this paper is an effective descriptor to represent the fatty tissue gray feature statistics, for the grayscale intensity values of different regions from the fatty tissue are always similar and has low similarity with other regions around the fatty tissue. Fig. 2 shows the partial enlarged viewing of Fig. 1, which the fatty tissue is different from the background regions.

Another important thing is determining the similarity between the unmarked regions and the marked fatty tissue regions. Bhattacharyya coefficient [21,22] is a simple yet efficient method to measure the similarity [15]. For each region, we calculate a 16-bin intensity histogram, which is then normalized to [0, 1]. Assume that $Hist_R$ represent the normalized histogram of a region R, and the similarity measure between region R and Q is denoted by $\rho(R, Q)$ which is calculated as

$$\rho(R, Q) = \sum_{i=1}^{16} \sqrt{Hist_R^i \times Hist_Q^i} \qquad (1)$$

where $Hist_R^i$ and $Hist_Q^i$ are the ith bin of the normalized histograms, respectively. According to Eq. (1), the larger the value of $\rho(R, Q)$ is, the higher the similarity is.
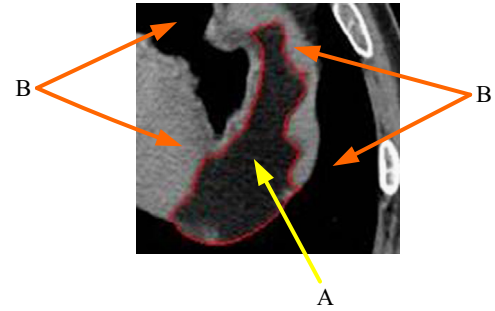
Fig. 2. An example showing lowing similarity between fatty tissue and background regions. It is the partial enlarged viewing of the Fig. 1. A is the fatty tissue and B is the other regions around the fatty tissue.

2.3. Fatty tissue extracting process

After marking the target, the image consists of marked fatty tissue regions $O = \{R_1^O, ..., R_i^O, ..., R_I^O\}$ and unmarked regions $N = \{R_1^N, ..., R_j^N, ..., R_J^N\}$. We merge the marked fatty tissue regions with unmarked regions. For each region $R_i^O \in O$, assume we find M adjacent regions $\{A_1, ..., A_m, ..., A_M\}$. For each region $A_m, A_m \notin O$, K adjacent regions $S_{A_m} = \{S_1^{A_m}, ...S_k^{A_m}, ..., S_K^{A_m}\}$ are found. It is obvious that $R_i^O \in S_{A_m}$. The similarity $\rho(A_m, S_k^{A_m})$ between A_m and each region in S_{A_m} is calculated using Eq. (1) and if they satisfy:

$$\rho(A_m, R_i^O) = \max_{k=1,...,K} \rho(A_m, S_k^{A_m}) \qquad (2)$$

A_m and R_i^O is merged into one region and A_m is labeled as the fatty tissue. Otherwise, they will not be merged. The process is executed iteratively until no new regions are merged. Therefore, OIIS can stop automatically without setting stop condition and all the unmarked regions are labeled as background. Finally, each region is labeled as one of the two classes: fatty tissue or background. The corresponding algorithm is shown in Algorithm 1.

Algorithm 1. The OIIS algorithm
Input: The initial over segmentation result and markers on object
Step 1: For each region $R_i^O \in O$, find the set of its adjacent regions $\{A_1, ..., A_m, ..., A_M\}$.
Step 2: For each $A_m, A_m \notin O$, find its adjacent regions $S_{A_m} = \{S_1^{A_m}, ...S_k^{A_m}, ..., S_K^{A_m}\}$.
Step 3: Calculate the similarity $\rho(A_m, S_k^{A_m})$. If it satisfies Eq. (2), then $O = O \cup A_m$. Otherwise, they will not be merged.