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A medical image segmentation algorithm based on bi-directional region growing

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ABSTRACT

Image segmentation is one of vital researching branches in medical image processing and analysis. Considering the characteristics of medical images, we propose a bi-directional region growing segmentation algorithm. The interests of the algorithm include the easiness of initial seed selection and robustness to noises and the order of pixel processing. This method also holds for other segmentation applications in which background region is simple but target region is complex. In order to select an appropriate threshold, the concept of Neighboring Difference Transform is proposed. The issue of threshold selection is converted to minimization problem with the assistance of statistical properties of transformation matrix. Experimental results show that the algorithm can accurately obtain medical image segmentation results.

1. Introduction

Image segmentation refers to the technique that partitions a digital image into multiple segments and is typically used to identify regions of interest (Regions of Interest, ROI) or other relevant information in digital images [1]. This paper investigates the segmentation problem for the medical images. Different from the traditional segmentation purposes, we focus on how to effectively separate the tissue region and the background region. The proposed segmentation algorithm could serve as the pre-processing of the following medical image processing.

Multi-modal medical image registration. Medical image registration plays an increasingly significant role in many clinical applications, such as the detection and diagnosis of diseases, planning of therapy, guidance of interventions, and the follow-up and monitoring of patients [2]. However, there exist large differences on the inner structure among various multi-modal medical images, which makes it difficult for precise registration. If medical images are segmented into the tissue and the background parts, we can make better use of the contour information for registration, which may tackle the problem brought by differences of the structural information [3].

3D surface rendering. In the process of 3D reconstruction of medical images, if we directly process the whole image, it will affect the recognition result and bring about dramatic time consumption. Such problem can be well addressed if the medical images are segmented to extract the interesting regions before reconstruction [4].

Medical image quality assessment. Both of the acquisition or storage may result in the visual distortion of medical images. Therefore, it is necessary to measure the quality of images to assess whether they meet the actual needs. As a matter of fact, we just focus on the quality of the parts containing useful information (namely the soft tissue parts), and neglect that of the background part. To achieve this effect, we need to segment medical images two parts.

Until now, there is no unified standard for the image segmentation classification. In literature [5], the authors presented a relatively explicit classification method, according which the existing image segmentation algorithms can be classified into four categories: (1) Local filtering approaches, (2) Snake and Balloon methods, (3) Region growing and merging techniques, and (4) Global optimization approaches based on energy functions or Bayesian and MDL (Minimum Description Length) criteria. The region growing algorithm is firstly proposed by Adams et al. [6]. The basic theory is that select a seed set first, and then combine the surrounding pixels containing similar morphologies (e.g. intensity and texture) with the seed. Update the seed set continually until the end condition is satisfied. As taking both visual feature and spatial distribution of the pixels into account, region growing algorithms can achieve better visual segmentation results. What's more, they

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are insensitive to the change of the inner regions, and the segmentation results can produce the closed regions [7]. Since the medical images can be roughly divided into two parts, the background part and the object part, and the object part is relatively complex in terms of morphologies, this algorithm is suitable for the medical image segmentation [8].

However, there are three problems plaguing the traditional region growing algorithms: (1) the segmentation results heavily depend on the order of the pixel processing; (2) it is difficult to automatically select the appropriate initial seed; (3) it is easy to be affected by noises and forms the region with holes. For the first problem, Mehnert et al. argued that all of the pixels that have the same minimum δ (a measure of the difference between a pixel and the intersected region) value should be processed in parallel to avoid the segmentation errors spurred by random serial processing [9]. For the second problem, Fan et al. proposed an automatic image segmentation algorithm by integrating color-edge extraction and seeded region growing [10]. In the algorithm, the edge detection is conducted on the image first to obtain the major geometric structures, and then the centroids of these adjacent edge regions are selected as the initial seeds. Shan et al. put forward a novel automatic seed point selection algorithm for breast ultrasound images [11]. Speckle reduction is made first; then select the segmentation threshold by an iterative method; finally, locate the lesion region and its approximate center point is taken as the initial seed. For the third one, the usual practice is to remove the noise by Gaussian filtering before segmentation [11,12]. However, this approach often causes two problems: (1) it is likely to result in edge blur which affects the segmentation result [13]; (2) if the noise-reduction is not complete enough, segmented regions will contain isolated holes. To eliminate holes, Pan et al. proposed to conduct the close operation to refine segmentation results [12].

In this paper, we propose a segmentation algorithm for the medical images, namely the Bi-directional Region-Growing-based (BRG) image segmentation. In the algorithm, the statistical information of Neighboring Difference Transform is used to determine the segmentation threshold. The interests of the algorithm involve robustness to the sequence of processing the pixels, easiness in selecting the initial seeds, and being free from noises.

The rest of the paper is organized as follows. In Section 2, we analyze the basic theory of image segmentation. First of all, the formal description of the image segmentation is given, then the drawback of traditional region growing algorithms is illustrated, finally, we propose the bi-directional region growing algorithm with the aim at tackling the existing drawback; in Section 3, the concept of Neighboring Difference Transform (NDT) is proposed to measure the intensity difference between pixels and their neighbors; Section 4 details the whole procedure of the newly-proposed image segmentation algorithm based on NDT, the rule of threshold selection is also given; Section 5 shows the experimental results, which justify the proposed algorithm; finally, we conclude the paper in Section 6.

2. Image segmentation analysis

2.1. Problem description

Let the set R denote the whole image region. The segmentation of R can be regarded as dividing R into N non-empty subsets (R_1, $R_2, \ldots, R_N$) which meet the five following conditions:

$$\bigcup_{i=1}^{N} R_i = R; \tag{1}$$

$$R(i) \cap R(j) = \emptyset \qquad \text{if} \quad i \neq j; \tag{2}$$

$$P(R(i)) = \text{TRUE} \quad (i = 1, 2, \ldots, N); \tag{3}$$

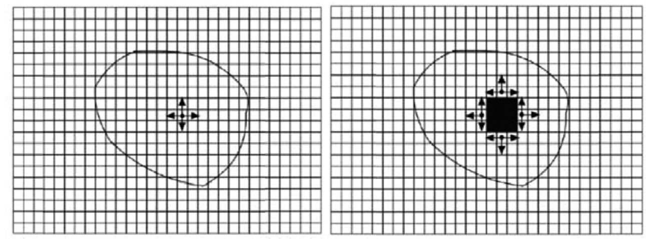

Fig. 1. Illustration of region growing based segmentation.

$$P(R(i) \cup R(j)) = \text{FALSE}, \qquad \text{if} \quad i \neq j; \tag{4}$$

$$\text{For any } i (i = 1, 2, \ldots, N), \quad Ri \text{ is connected.} \tag{5}$$

2.2. The traditional region growing (RG) algorithm

Steps of region growing algorithm are as follows:

Step. 1 Select a seed, and push it into the queue Q.

Step. 2 Check all the pixels around the seed to determine whether they are similar to the seed one by one. If so, push the pixel into Q, otherwise disregard it.

Step. 3 Pop the first pixel from Q and add it to the set R_1. Check whether Q is empty. If not, take the first element from current Q as the seed, and repeat Step 2. Otherwise, push the elements which are not yet added to R_1 to the set R_2. Fig. 1 shows an example of region growing based image segmentation.

Proposition 1. For an image R, let p denote the initial seed, after region growing, the region R_1 generated from p ($p \in R_1$) is connected.

Proof. (Contradiction) Assume that R_1 is unconnected, then there are at least two subsets $R_{1,1} \subset R_1$, $R_{1,2} \subset R_1$, and $R_{1,1} \cap R_{1,2} = \emptyset$ Setting the seed $p \in R_{1,1}$, as $R_{1,1} \cap R_{1,2} = \emptyset$, the algorithm ends after finishing the search of the subset $R_{1,1}$, we get the result $R_{1,2} \not\subset R_1$. However, the result is paradoxical with the assumption. So, the proposition is correct, namely, R_1 is connected.

From Proposition 1, notice that traditional region growing based algorithm can only guarantee the connection of the regions that the initial seed is in, but fails in other regions. As the algorithm is always affected by noise or irregular edges, it tends to divide noises into small isolated regions and produce many small isolated regions around edges. As shown in Fig. 2, the subfigure (a) shows a brain CT image; its segmentation result obtained by region growing algorithm is shown in subfigure (b). (c) And (d) present the enlarged versions of the image blocks in the two red boxes in (b).

As a matter of fact, in Fig. 2, all the isolated regions belong to the background region. To solve the problem, we proposed an improved region growing segmentation, namely Bi-directional Region Growing (BRG) based segmentation algorithm.

2.3. Bi-directional region growing

Actually, Bi-directional Region-Growing-based (BRG) algorithm contains two region growing. In BRG image segmentation algorithm, the first region growing is same with the traditional one elaborated in Section 2.2, it aims to get a rough segmentation result. Through analysis we can see that the segmentation which contains the initial seed is connected; however, other segmentations may be unconnected. It will produce many small isolated points around the image edge. Therefore, we make a second region growing to remove the isolated regions produced by noise or weak edges. BRG algorithm is defined as follows:

Step 1. Select a seed, and push it into the queue Q.