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Synergistic integration of graph-cut and cloud model strategies for image segmentation

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ABSTRACT

This paper proposes a new graph cut image partitioning method that calculates image data using cloud model for constructing the objective functions (GC-CM). In the objective function, it contains a boundary preserving smooth term and a data item which evaluates the deviation of each pixel that belongs to different regions. The core method models the foreground object and background of the images as cloud models by the back cloud generator. The data item is calculated with the X-condition cloud generator. We use the membership degree between each pixel to calculate the similarity of the neighbor pixel established as the smooth term. The energy minimization is completed with the minimum cut theory and the graph cut iterations. In contrast to segmentation results with discontinuous edges using conventional graph cut method, this method has better generality and accuracy. Experiments on different data sets including natural images from Berkeley database, synthetic data, and medical images suggest that the proposed method based on cloud model and graph cuts outperforms other state-of-the-art approaches.

1. Introduction

Image segmentation is widely used in medical image analysis, image processing, remote sensing, intelligent transportation, product testing, computer vision, etc. [1]. In various forms, the target image can be divided into several identifiable targets or can be divided into several regions which have some consistency. The image segmentation methods mainly include four categories: threshold-based, edge-based, region-based, and energy-based.

Threshold-based approaches are the simplest and the most efficient ones among all the existing segmentation methods. It is a challenging task for choosing the threshold which can separate the image into two groups directly. The existing threshold-based methods mostly can be converted into the segmentation criterion function optimization, so it is a current research hotspot to explore all kinds of intelligent optimization algorithm in the application of threshold-based methods. The extensive research of intelligent optimization algorithm was genetic algorithm and artificial neural network, etc. Payel [2] proposed a genetic algorithm for combining representations of learned information to perform automated three-dimensional segmentation, which performs satisfactory segmentation of the pelvic CT and MRI images. Ailing [3] proposed an adaptive vector quantization method, in which the self-organizing map network and vector quantization method are integrated together, and the method was applied to segment the human brain MRI images with excellent performance and efficiency.

Edge-based method [4] is a segmentation algorithm on the basis of image edge information, which includes edge detection operator, edge relaxation, boundary scouting, Hough transform, etc. The edge detection is usually accomplished with the aid of convolution between the spatial differential operator and the image. The edge relaxation method takes into account the nature of the edges in the context of adjacent edges, and increases the local edge strength if there are sufficient features of the boundary. The boundary scouting method determines the global optimal boundary according to the defined optimality criterion, that is, the edge detection process is transformed into the problem of searching for the optimal path in the weighted graph. The Hough transform method is suitable for detecting objects of known shape in an image. Edge-based algorithm can achieve better results for less complex images such as sharper edge noise and less noise, but the results exists edge discontinuity, edge blur, edge loss, and poor anti-noise ability for complex images problem.

Region-based methods are advantageous because they reduce the computation demand by working on regions instead of pixels. In recent years, some researchers considered the advantages of the segmentation method based on edge and region, and proposed the image segmentation method through comprehensive utilization of image edge and regional characteristics [5,6], which improves classification accuracy.

Energy-based methods get segmentation result by minimizing the energy function. It includes level sets, graph cut, iterated

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conditional mode (ICM), etc. The energy functions for image segmentation are often difficult to minimize. The level set method was independently introduced by Caselles et al. [7] and Malladi et al. [8] in the context of active contour models for image segmentation. But it can cause numerical errors and eventually destroy the stability of the level set evolution. To overcome this limitation, Osher et al. [9] employed reinitialization to restore the regularity of the level set and to maintain stable level set evolution. However, the practice of reinitialization not only raises serious problems as when and how it should be performed, but also affects numerical accuracy. Chunming Li [10] proposed a new variational level set formulation. In its numerical implementation, relatively large time steps can be used in the finite difference scheme to reduce the number of iterations, while ensuring sufficient numerical accuracy. Xiao [11] proposed an efficient and robust level set method by introducing the multi-scale segmentation idea into the local region-based method, which have excellent efficiency and robustness. ICM [12] is a simple coordinate descent approach for minimizing the energy defined by a Markov random field. While it is very sensitive to the initial values and has low numerical accuracy. Therefore, Zoran [13] proposed a Gentle ICM which makes a few modifications to ensure a more 'gentle' descent during the first iterations of the algorithm. It has substantial performance improvements. Graph cuts method has been extensively applied to image segmentation since Boykov et al. [14] published an article in 2000. Graph cuts method has become an accurate and useful tool for image segmentation. The graph cuts method can achieve globally optimal result which combines global and local information. It has high stability and speed. But the binary image is obtained through the gray level information, whose segmentation result is poor for the weak edges of images and the edges discontinuous of the segmentation result. Due to the limitation of medical imaging equipment, medical images are often corrupted by noise and boundaries of the target and background are blurred [15]. There exists much intensity uneven or boundary fuzzy in the medical images. These shortcomings make the traditional graph cut method fail.

Much research works based on graph cuts are studied in Refs. [16–19], and their superior performances and robustness over each of the components are beginning to be well demonstrated. Cloud model [20] is a model to use the language to describe the uncertainty conversion between qualitative of the concept and it value. It firstly combines the fuzziness and the randomness, and then forms an intermapping between the qualitative and quantitative information. It is an approximate normal distribution rather than a strict normal distribution. For a random variable, its membership degrees are multiple, which fit a probability distribution. And its characteristic can well solve the poor edge segmentation faults. Combining advantages of graph cuts and cloud model in this paper, we propose a new image segmentation method based on Graph Cut Cloud Model (GC-CM). To evaluate the superiority of the proposed method GC-CM, we perform the segmentation method on synthetic data, natural images from the database Berkeley and real medical images.

In the rest of this paper, in Section 2, we elaborate the complete methodology of the delineation algorithm. In Section 3, we describe an evaluation of this method in terms of its accuracy and efficiency. In Section 4, we summarize our contributions and conclusions.

2. Materials and methods

2.1. The traditional graph cut model

Graph cut is a very useful and popular energy optimization algorithm, it can not only enrich the application of image segmentation, but also has important significance in the research of image retrieval [21].The segmentation theory is derived from the clustering algorithm. It transforms the image to the weighted graph $G=(V, E)$, and then divides G into Ψ areas. It can be described as searching for Ψ set fields $\{\Pi_i\}_{i=1}^{\Psi}$, which does not overlap between any two regions, and $\Pi_i \cap \Pi_j = \emptyset \ \ (i \neq j)$ [22]. Please refer to Table 1 for important definitions used throughout the rest of this paper.

Table 1.
Important notation and terms used in this paper.

G,V, E,P	The weighted graph, the vertices set, the edges set, the non-terminal vertices set, respectively
S,T	The foreground, the background, respectively
Ψ	A set of segmented regions
Π_i	The region is marked as i
I_p, μ_p	The grey level of the pixel p, the membership of pixel p, respectively
μ_p^S, μ_q^T	The membership of pixel p belong to the foreground, the membership of pixel p belong to the background, respectively
$D(\lambda)$, $R(\lambda)$	The data item, the smooth item, respectively
Ex, En, He	Expectation, entropy, hyper-entropy, respectively
CG^{-1}, CG^x	The backward cloud generator, X-condition cloud generator, respectively

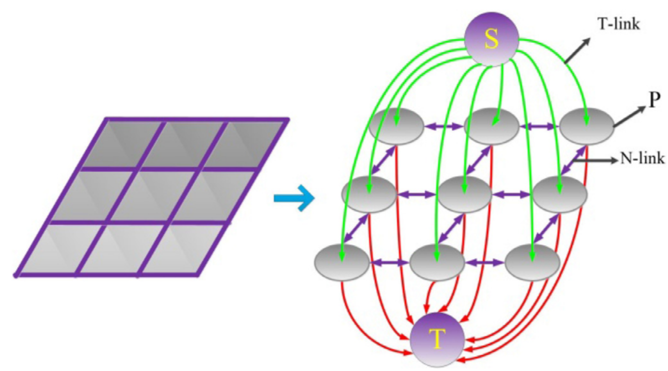

Fig. 1. Graph cut model diagram.

The graph cut model diagram is shown in Fig. 1. The vertices $v \in V$ in G are corresponding to a pixel in the image. The vertices can be divided into two categories: (1) The terminal vertices set $\{s, t\}$ consists of the source point which represents the characteristics of the foreground region and the end point which represents the characteristics of the background region. (2) The non-terminal vertices set P consists of other pixels which are the non-source point and the non-end point. So the vertex set can be expressed as $V = P \cup \{s, t\}$. The edge set $e \in E \subseteq V \times V$ is composed of two kinds: (1) The edges (p, s) and (p,t) are formed the pixels point p and the terminal vertex $\{s, t\}$, called T-link, of which weights represent the reasonable degree of the pixel belongs to foreground and background respectively. They are corresponding to the data item in the energy function. (2) The edges $(p, q) \in N$ are formed by the edges between adjacent non-terminals vertices, called N-link, of which weights represent the discontinuity between adjacent pixels on the gray level. It is corresponding to the smooth item in the energy function. So the edge set can be expressed as $E = N \cup \{(p,s), (p,t)\}, \ \ p \in P$.

N is an edge set $\{(p, q) \in N, p \in P, q \in P\}$ between adjacent pixels in G. The marking function is defined as $\lambda(p) = b, \ b \in B$, which $B \subset N$ is a positive integer. The data item $D(\lambda)$ is used to measure the price of different pixel, and the point p is marked as $\lambda(p)$, which is used to constrain the consistency of the data. The smooth item $R(\lambda)$ is used to measure the price of adjacent pixel points. For example, the p and q are marked as $\lambda(p)$ and $\lambda(q)$, which is used to constrain the similarity of the neighboring pixels in image data. Then the final mark result can be