CT Image Segmentation based on Clustering and Graph-Cuts

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Abstract

In order to complete the auto-segmentation of cardiac dual-source CT image and extract the structure of heart accurately, this paper proposes a hybrid segmentation method based on k clustering and Graph-Cuts. This method identifies the initial label of pixels, on the basis of it, then creates the energy function on the label with the knowledge of anatomic construction of heart and constructs the network diagram, finally minimizes the energy function by the method of max-flow/min-cut theorem and picks up region of interest. The experiment results indicate that the robust, accurate segmentation of the cardiac DSCT image can be realized by combining Graph-Cut and k clustering algorithm.

1. Introduction

With the improvement of people’s living standard and life expectancy, cardiovascular disease has been the important cause of death, so the early diagnosis of cardiovascular disease can decrease the rate of deaths [1]. The development of CT technology, especially Siemens Dual Source CT (DSCT) improves the time resolution obviously, furthermore, it reveals good application potentials in the microstructure of heart [2]. This paper gather the cardiac image through DSCT and segment the main structure of cardiac...
images. The accurate segmentation of DSCT images provides a good base for reconstructing anatomy of the heart and giving clinical visual reference data and assessment.

Clinical medical image has an extremely intricate diversity and complexity, because of the inherent characteristics of the various imaging devices; it leads the image to cause some certain noise, field shift effect and body effect; besides, it leads the objects margins of interested to be unclear, and the medical image, especially the CT image segmentation to be a challenge task. The common methods of medical image segmentation include threshold value, edge-based method, region-based method and morphology-based method. All these methods are difficult to achieve the ideal effect in the segmentation of high noise and low contrast image of heart. The paper [3] propose a snake model based generalized gradient vector flow, this method realize precise segmentation of MR left ventricle images. Graph-Cuts is a key application of Graph theory, it applies in many fields such as physics, chemistry, cybernetics, network theory and computer science, etc [4]. In 2001, BoyKov Y, proposed the fast calculation method of max-flow/min-cut, and realized the extraction of the target framework based on minimized energy [5]. This calculation method has many features such as fast, robust, global optimization, strong anti-noise and good extensibility, etc. It not only applies in the segmentation, but also provides a unified idea for treatment of other visual problems [6]. K-means clustering algorithm was raised by Mac Queen in 1967. It is a basic partitioning method in the analysis of cluster. It is simple and it has the fast convergence speed; besides, it has a strong ability of local research and can process large data sets effectively. The disadvantage of the method is that it has strong sensitivity to the initial value of the cluster, and it is easy to fall in to local optimum [7].

As for the features of medical CT images, this paper combines the advantages of Graph-Cut and the k clustering, extracts the global and local information of image effectively, and decomposes the complex problems so as to improve accuracy and speed of segmentation. The second part in this paper introduces Graph-Cut and k clustering. The third part will describe the new strategies of segmentation and energy function in detail. The final part will analyze the results.

2. k clustering and Graph-Cuts algorithm

2.1. k clustering algorithm

Clustering algorithm belongs to unsupervised learning; it doesn’t depend on any predefined class and class label. At the time of processing a great mass of data, the cost will be comparatively less [8]. K clustering algorithm determines the dissimilarity between the two elements by quantify calculating Minkowski distance, the definition of Minkowski distance (E) is:

\[ E = \sum_{j=1}^{k} \sum_{i=1}^{L} \| C_j - X_i \|^p \]  

(1)

K is the number of clustering center points, L stands for the number of pixel dot. Some measurements or scalar often used in dissimilarity include Euclidean distance and Manhattan distance, and Euclidean distance and Manhattan distance can be considered as the special case of Minkowski distance when p=2 and p=1.

K clustering algorithm is to set the number of pre-classification (k), and choose k objects as the initial clustering center from n data objects, and leave the other data objects, and distribute them to their most similar clustering centers according to the similarities between the clustering centers and them. As shown below, \( X_p \) belongs to the sort of \( \theta_i(m) \).

\[ X_p \in \theta_i(m) \quad \text{if} \quad \| X_p - C_i(m) \| < \| X_p - C_j(m) \| \quad \text{for} \quad i = 1,2, \ldots, k, i \neq j \]  

(2)
After finishing the distribution, re-calculate every newly-get clustering center (clustering center should correspond to the mean value of every object of this clustering center); repeat this course until the standard measure function begins to convergent, each center point doesn’t change anymore. Clustering has the feature of compaction in the same kind of clustering, and the feature of separation in different kinds of clustering.

2.2. The algorithm of Graph-Cuts

The CT image will be transferred into the directed network figure shown as $G(V, E)$, $V$ stands for a series of vertexes, corresponding to the pixels in the CT image; $E$ stands for a series of edges, corresponding to the connection between pixels. $(p, q)$ Shows from vertex p to q, and $G(V, E)$ shows the weight connecting vertex p to q. Generally, The pixels of the image corresponds to the vertex of network, the difference and similarity between pixel correspond to the cost of edges, by the above way map the image as a network which makes the cost of the network cutting correspond to the energy function of visual problems.

Suppose using $f$ to mark the vertexes in the above directed image $G$, $f \in \{1, 2, \ldots, q\}$ and q is the total number of label, so the state of each vertex in the whole image $G$ can be expressed as $F = \{f_1, f_2, \ldots, f_N\}$, and $N$ represents the total number of vertexes.

In order to calculate every label of the pixel, firstly construct an energy function of labels ($F$), according to the data constraint and smooth constraint, the energy function based on Potts model is:

$$E(F) = E_{data}(F) + E_{smooth}(F) = \sum_{p \in P} D_p(f_p) + \sum_{\{p, q \in N\}} D_{p, q}(f_p, f_q)$$

$$E_{data}(F)$$ is the data item, which is used to measure $F$ and the discordance of the data observed. $E_{smooth}(F)$ is the smooth term, which is used to measure the smooth degree of $F$, $N$ stands for the collection constructed by adjacent pixel pairs, $D_p(f_p)$ is the probability of $f_p$ when the pixel is marked as $p$. $D_{p, q}(f_p, f_q)$ is the similarity between pixel $p$ and $q$.

![Figure 1: segmentation of a directed capacititated graph](#)

The basic concept of image Based on Graph-Cuts is to describe the image segmentation as a minimum problem about energy function. As shown in figure 1, set each pixel in the image as a node, and reset a virtual source and sink.
In order to get the best segmentation, the global energy form should be minimized. The source \( \{s\} \) and sink \( \{t\} \) in the method of Graph - Cuts correspond to the target pixel and background pixel. Through the transformation from image to directed image \( G \), the segmentation is about the division of all the vertexes in connection with target and background pixel, and find out the minimum cost cut about \( G \).

3. The Segmentation algorithms based-on \( k \)-means and Graph - Cuts

3.1. The Establishment of Graph-Cut Model

CT value of CT medical images is to show the density of organization and CT value is divided into 2000 units, CT value of water is 0, and CT value of air is -1000; CT value of compact bones is 1000. According to the clinical experience, CT value of cardiac muscle tissue, generally, is about -240. Because of the complexity of the structure of heart and the similarity between it and the neighboring soft tissues and cardiac muscle, the segmentation is comparatively difficult. According to the characteristics of CT image, the original energy function is not fit for the segmentation of CT image. So here introduce local information based on target seed. The definition of the edge terms is:

\[
E_{p,q} = g(p,q) \cdot |u_p - u_q| 
\]

(4)

\[
g(p,q) = \exp\left(-\frac{\|I(p) - I(q)\|^2}{2\sigma^2}\right)
\]

(5)

In the formula (5), \( I \) stand for the intensity of pixel, namely, CT value.

Definition of the regional option of energy function:

\[
\begin{align*}
E_p(u_p = \text{"bkg"}) = & -\log [P_p(I(p) \in O) \times \exp\left(- \left(\frac{d(p,O)}{\sigma_a}\right)^2\right)] \\
E_p(u_p = \text{"obj"}) = & -\log [P_p(I(p) \in B)]
\end{align*}
\]

(6)

In the formula (6), \( O \) and \( B \) are the target and background seed point, probability density computation according to the Markov random field model and Bayes theorem, The function \( d(p,O) \) shows the distance between pixel \( P \) and target seed point, \( c_a \) defines the influence of the expansion and region of the seed point, In this paper, suppose , \( c_a = 10 \) is about 10. And the distance \( d \) is:

\[
d(p,O) = \min\{d(p,q) | q \in O\}.
\]

Show the distance of two points, use Euclid geometry distance or Geodesic distance to calculate.

3.2. The solving method of model

First transfer the image \( I \) from the 512×512 matrix form into One-dimensional array with 262044 elements; As for the One-dimensional array of CT values, use the algorithm of method of \( k \) clustering and get every cluster number of the pixels relevant; by \( K \) means clustering, all the CT image pixels (262,144 pixels) are divided into \( k \) clustering, so that the similarity in the same clustering pixels is comparatively high, the similarity of different pixels is lower. The \( K \) means clustering of CT values is mainly used for the coarse segmentation of CT image. And then calculate the data term and smooth term that are needed in the energy function; The calculation of the data term adopts the variance-covariance matrix of the CT
image with the same number of the clustering; get the information that reflects the degree of trend of the CT image in the statistical sense, what is the probability of every pixel in the image to belong to some kind of clustering area. Smooth term uses Gauss and Sobel filtering, the two-dimensional convolution to operate on the smoothing and edge detection of CT image, and calculate the result of the smooth term. The calculation of smooth term is mainly to keep the margin. And then use the max-flow/min-cut algorithm to minimize the energy function so as to get the result of min-cut in the image.

4. Analysis of the result of the experiment:

We have collected 300 cardiac images of DSCT, and performed graph cut segmentation with \( k \) clustering. The experimental results demonstrate that the above method is highly efficient and that new cost functions improve accuracy considerably.

The environment for this experiment is Intel Core2 7400, with 4G memory, and the operating system is Win 7, the computer aid adopts MATLAB 2009b, the data of CT image output by DSCT adopts the standard DICOM3 format, the size of the image is \( 512 \times 512 \), the grayscale level of the pixel is 12 bits, that is 0-4096, the image’s spatial resolution is \( 1 mm \times 1 mm \times 1 mm \).

In order to realize the good clustering of various structures of tissues, by experiment, determine the number of k-means clustering. As is shown in the Table 1, with the number of clustering and the margin relevant to the boundary increasing, the smooth numbers obviously, however, the data cost is related to the CT value, so it doesn’t change a lot. Computation time increases with the total cost when segmenting, the response increases.

| Region Number \( k \) | Smooth Cost | Data Cost | Computing Time(s) |
|------------------------|-------------|-----------|-------------------|
| 2                      | 0.0076      | 1.3092e+005 | 0.5798           |
| 3                      | 1.5529      | 1.2583e+005 | 0.9172           |
| 4                      | 4.2714      | 1.1339e+005 | 1.3477           |
| 5                      | 4.7926      | 1.2318e+005 | 1.8809           |
| 6                      | 18.4284     | 1.1816e+005 | 2.1190           |
| 7                      | 25.0507     | 1.1880e+005 | 2.5074           |
| 8                      | 23.5622     | 1.2179e+005 | 3.0004           |

The segmentation results are shown in the figure 2. Fig. 2 depicts a comparison of actual segmentation for the method. The segmentation results are different according to the region number. Compared with the original image when \( k=4 \) or \( 5 \), it will have a better result. Considering the computation and quality of cutting, \( k \) should be 4.

5. Conclusion:

This paper, combining with the features of DSCT image and the Gradient Computation as well as the form features to segment, uses Graph-Cuts to realize the preliminary cut of the interesting region of heart image. This method gathers the gradient of the DSCT image and the form feature into the same framework of probability; furthermore, constructs the energy function combining the features above. Using the min-cut algorithm to segment the DSCT image can get a good result; the calculation is simple,
and also it is fast and has a good robust. Next, integrate more energy function of image according to the feature design of the DSCT image so as to realize accurate cut of the graph of heart.

**Figure 2:** Effects of graph cut and clustering with different value of k

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