AN EFFICIENT SEGMENTATION AND ANALYSIS OF CT LUNG IMAGES USING GRAPHCUT TECHNIQUE

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Abstract— Lung segmentation is often performed as a preprocessing step on chest Computed Tomography (CT) images because it is important for identifying lung diseases in clinical evaluation. Hence, research on lung segmentation has received much attention. Computer aided diagnosis system provides early lung diseases diagnoses. Till today, a large number of techniques available that can extract the required foreground from the background. However, most of these methods are only based on regional or boundary information which has limited the segmentation result to a large extent. The graph cut based segmentation method is proposed, it has obtained a number of attention because this method use both regional and boundary information. This graph cut segmentation technique uses mincut algorithm to separate lung from the background .The proposed lung segmentation technique segmented the CT Lung images accurately. The result of segmentation can help radiologist in early diagnosing lung diseases. The graph cut algorithm can also applicable for some other pathologies in other parts in human body, such as liver, brain.

Keywords—mincut; graph cut

I. INTRODUCTION

Image segmentation is partition of an image into different regions which may have similar color, intensity or texture. Segmentation as a preprocessing step plays a significant role in computer vision, object recognition, tracking and image analysis. Conventionally, segmentation can be grouped into five categories. The first one is threshold based segmentation method. This method usually divides the image into two parts namely foreground and background. When the intensity of the pixels is larger/smaller than a predefined threshold, those pixels are classified as foreground. Otherwise, they will be viewed as background. Threshold based approaches are the simplest, easiest and fast ones among all of the existed segmentation methods. The difficulty is that it is not easy to find an appropriate threshold which can separate the image into two groups directly. This method also requires the foreground and background in the image have obviously different intensity values. Otsu's algorithm is the most popular method for finding an appropriate threshold. Otsu's algorithm can find a threshold which may make the inter-part (between foreground and background) variance maximal and the intra-part (within foreground or background) variance minimal. The second category is edge based segmentation scheme. This method assumes that the values of the pixels connecting foreground and background are distinct. These discontinuities are usually detected by the first or second order derivatives method like gradient and Laplace. Sobel, Roberts and Rrewitt edge detectors, which are based on the gradient concept, are easy to be implemented and can roughly detect the contour profile but they are sensitive to the image noise.

The Laplace algorithm uses the second derivative to detect the edge which can localize the direction of the pixel along the edge but it is also sensitive to the noise. The LoG (Laplace of Gaussian) was introduced to reduce the effect of noise by smoothing the image with a Gaussian filter then utilize the Laplace operator. Canny edge detector was reported to have better detection result compared with previous ones since this method have combined the operation of filter, enhancement and detection. Even though the boundary of the object can be detected by these proposed methods, many false edges will be included. Thus, post-processing operations are usually needed for the edge-based segmentation.

The third category is region-based segmentation. The typical algorithms are region growing and region splitting-merging. For region growing scheme, a set of seeds are needed to be identified firstly. Then, the neighbouring pixels are grouped to these seeds through predefined criteria such as by the similar intensity, color or texture. Hence, the skill of the selection of seed points is very important for region growing when no more prior information is known. For the region splitting-merging method, an image is first divided into a series of small regions. Then merge or split these smaller regions by a prerequisite condition.

The procedure can be described as splitting of the image into many un-overlapped regions until it cannot be split anymore. Then, merge the adjacent regions that satisfy with a predefined condition. Region-based segmentation strongly relies on the intensity value of the object and background and it always produce un-smooth boundary for the extracted object. The forth category is watershed based segmentation. This method views the image as topological surface and the intensity value as height. The regional minimal values in the image are interpreted as catchment basins and the maximal values between every two neighbouring catchment basins are viewed as ridge line.

Watershed-based segmentation is to find the ridge line called watershed within the image. So, in order to extract the object, watershed transform algorithm is usually applied to gradient image where the object is corresponding to However, direct application of watershed algorithm will have over-segmentation problem due to the noise and other local irregularities of the gradient. Marker-controlled watershed segmentation is to reduce the over-segmentation. In this method, the regional minimal values only occur at the location of the markers.

Thus, the key procedure is to identify the markers which include internal and external markers. Internal markers denote the object while the external markers represent the background and these external markers must be connected. When the markers can be identified appropriately, watershed based segmentation can obtain reasonable results. The fifth category is energy based segmentation. This method need to establish an objective (energy) function which will reach a minimal value when the image is segmented as expected result. Live wire, active contour, level sets and graph cut are all grouped into this category.

An interesting source of images is in the medical field. Here, imaging modalities such as CT (Computed Tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography) etc. generate a huge amount of image information. Not only does the size and resolution of the images grow with improved technology, also the number of dimensions increase. Previously, medical staff studied two-dimensional images produced by X-ray. Now, three dimensional image volumes are common in everyday practice. Even four dimensional data (three-dimensional images changing over time, i.e. movies) is often used. This increase in size and dimensionality provides major technical challenges as well as cognitive. Automatic, or semi-automatic, algorithms are of interest.

Developing algorithms for medical image analysis requires thorough validation studies to make the results usable in practice. This adds another dimension to the research process which involves communication between two different worlds - the patient-centered medical world, and the computer centered technical world. The symbiosis between these worlds is rare to find and it requires significant efforts from both sides to join on a common goal.

The aim of this work is to develop a segmentation method for medical imaging applications. In particular, the segmentation of lungs from CT images. The motivation for this work is to increase the segmentation accuracy that are used to increase patient safety by providing better and more precise data for medical decisions, and can directly provide explicit lung regions without any post processing operations even in complex scenarios. The segmentation of lung parenchyma is an initial processing step, it is very important in the clinical diagnosis. Most of the methods in the present are a combination of a variety of methods, and are time-consuming, and it cannot get the segmentation result at once, and require multiple steps. This multiple steps are avoided by graph cut algorithm with GMM.

II. METHODALOGY

The focus of this work is segmentation of lungs on chest CT images and improves the accuracy. Lung segmentation is the basic first step for chest CT images that will be used for subsequent analysis, such as early lung disease detection or local area analysis. Improve the accuracy by using graph cut segmentation. Figure 3.1.1 describes this work. Input image is a CT lungs image that format can be anything like JPEG, RGB etc. Because that are converted into gray images which is involved to some preprocessing work like smoothing and etc. Size of image is varied from one to another but we don't change anything because it is not possible in medical image processing. In this project used only the size of less than 512x512 images.

A. GAUSSIAN SMOOTHING

All images has a noise but we want only noiseless images for processing so images are involved to a smoothing process. Lot of smoothing technique is available like Gaussian, exponential and etc. Gaussian smoothing is suitable for medical images so that are used in this project. The imaging machinery, environmental conditions, and other external interference, there will be inevitably noise when the CT images are created. This existing noise causes difficulties for the analysis, and it affects the segmentation accuracy.

Hence the first step in CT image process is to remove the noise. Commonly used CT image processing methods for noise reduction are mean, median, or Gaussian filtering. To improve the accuracy of segmentation of the lung pulmonary region, the Gaussian filter with the Gaussian kernel radius r=0.5 is adopted in our experiment. With that parameter the noise of the CT images can be removed and the contour of lungs can be kept clear.

B. SEED POINTS SELECTION

Seed point is nothing but it is the pixels value of image. In this project want 2 seed point one from background value and another from object/foreground. Finally all pixels are labeled based on this 2 pixel values. The value of the pixel is a number that corresponds to the intensity of the image. Seed point selection can do manually or automatically but in this project it's done by automatically. Graph is making by using some technique then assigns the weight. Weight can be assign by various methods. Every methods take various time but here by using a GMM it's take a less time for processing.

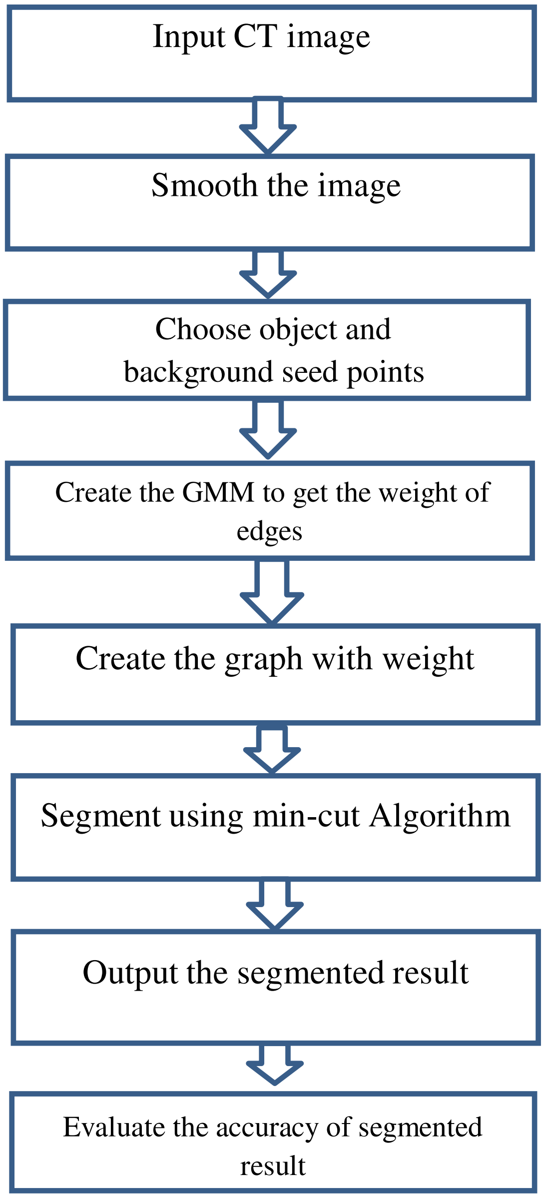

Figure 3.1.1 overall process

C. GENARATION OF GMM

Each seed point region is modeled using GMMs with K subclasses. Because lung CT images are gray scale images, the value of the pixel is a number that corresponds to the intensity of the image. Let x be a random variable that takes the value. To determine the probability model, a mixture of Gaussian distribution of the following form [1] is

$$Pr(x) = \sum_{k=1}^{K} \beta_k \cdot N(x; \mu_k, \sigma_k^2) \qquad (1)$$

Where K is the number of components, β are weights. And N (.) is the Gaussian probability density function (PDF) parameterized by mean value μk and standard variance value σk2:

$$N(\mu_k, \sigma_k^2) = \frac{1}{\sqrt{2\pi}\sigma_k} \exp\left\{ -\frac{(x_i - \mu_k)^2}{2\sigma_k^2} \right\} \qquad (2)$$

To perform the parameterized learning of the interactive a priori knowledge mixed model, the EM algorithm is usually the best choice. It not only provides initial robust and strong arguments, but also provides maximum likelihood estimation. Furthermore, compared with the K-means algorithm, the EM algorithm is more suitable for graph cuts, which is just a maximized likelihood segmentation model. Here, use the EM-MAP (Maximum a Posteriori) method [1], and the process is defined as below:

1. *Initialization*: $\Theta^{(0)} = \left\{ \beta_1^{(0)}, \ldots, \beta_K^{(0)}, \mu_1^{(0)}, \ldots, \mu_K^{(0)}, \sigma_1^{(0)}, \ldots, \sigma_K^{(0)} \right\}$
2. *E-step*: let $\gamma(i,k) = \beta_k Pr(x_i | \mu_k, \sigma_k) / \sum_{j=1}^{K} \beta_j \, Pr(x_i | \mu_j, \sigma_j)$;
3. *M-step*: $N_k = \sum_{i=1}^{N} \gamma(i,k)$; $\mu_k = (1/N_k) \sum_{i=1}^{N} \gamma(i,k) x_i$;
   $\sigma_k = (1/N_k) \sum_{i=1}^{N} \gamma(i,k)(x_i - \mu_k)^2$; $\beta_k = N_k / N$;
4. Iterate steps 2 and 3 until an arbitrary error is reached: $e = L(\Theta)^{i+1} - L(\Theta)^i < \varepsilon$;
5. Calculate the final Θ^*.

Because EM is an unsupervised parameter estimation method, the initial values of the model parameters should be given, and the methods result is sen-sitive to these initial values. Therefore, in the initialization step, here use the K-means clustering algorithm to determine the initial values, including mean value, variance, and weight factors. Using the above EM-MAP algorithm, Can determine the posterior probability for every interesting region in the CT image. The regional penalty Rp(.)in formula (9) can then be written as follows

Rp(1)=-lnPr(Ip|'obj') (3)

Rp(0)=-lnPr(Ip|'bkg') (4)

Furthermore, the boundary penalty B{p,q} in formula (6) uses an ad hoc function as follows:

$$B_{\{p,q\}} \propto \exp\left(-\frac{(x_p - x_q)^2}{2\sigma^2} \right) \cdot \frac{1}{\mathrm{dist}(p,q)} \qquad (5)$$

The energy function of (8) can then be rewritten as follows:

$$E(A,K,\Theta^*)) = \lambda \cdot \left\{ -\sum \log(Pr(A_p|K,\Theta^*)) \right\} + \sum B_{\{p,q\}} \cdot \delta(A_p, A_q) \quad (6)$$

With the region penalty and boundary penalty values, can create the graph for the CT image (as shown in Figure. 3.6.1) and segment using the minimum cut algorithm (7).

D. GRAPH CUT ALGORITHM

Let an undirected graph be denoted as G=< V, E > where *V* is a series of vertices and E is the graph edge which connect every two neighbor vertices. The vertex V is composed of two different kinds of nodes (vertices). The first kind of vertices is neighborhood nodes which correspond to the pixels and the other kind of vertices are called terminal nodes which consist of ***s*** (source) and t (sink). This kind of graph is also called s-t graph where, in the image ***s*** node usually represents the object while t node denote the background. In this kind of graph, there are also two types of edges.

The first type of edges is called nlinks which connect the neighboring pixels within the image (Here adopt 4-connected system in the 2D image). And the second type of edge is called t-links which connect the terminal nodes with the neighborhood nodes. In this kind of graph, each edge is assigned with a non-negative weight denoted as *e w* which is also named as cost. A cut is a subset of edges E which can be denoted as C and expressed as $C \subset E$. The cost of the cut $|C|$ is the sum of the weights on edges C which is expressed as follows[4].

$$|C| = \sum_{e \in C} w_e \quad (7)$$

A minimum cut is the cut that have the minimum cost called min-cut and it can be achieved by finding the maximum flow the graph is divided by this cut and the nodes are separated into two disjoint subsets S and T where $s \in S$, $t \in T$ and $S \cup T = V$. The two subsets correspond to the foreground and background in the image segmentation. This kind of graph can be depicted in Figure 3.5.1[4].

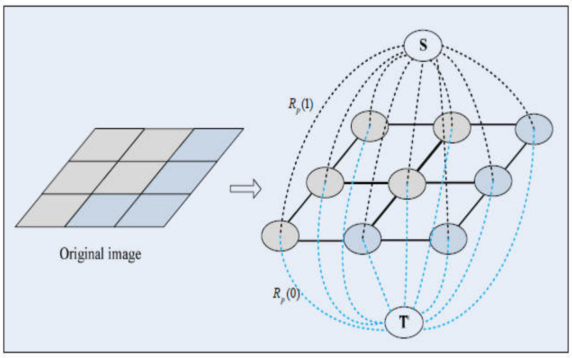

Figure3.5.1. Illustration of s-t graph. The image pixels correspond to the neighbor nodes in the graph (except s and t nodes). The solid lines in the graph are n-links and the dotted lines are t-links.

3.6 GRAPH CUT SEGMENTATION

Image segmentation can be regarded as pixel labeling problems. The label of the object (s-node) is set to be 1 while that of the background (t-node) is given to be 0 and this process can be achieved by minimizing the energy-function through minimum graph cut. In order to make the segmentation reasonable, the cut should be occurred at the boundary between object and the background. Namely, at the object boundary, the energy (cut) should be minimized. Let L= { l1,l2,l3, ···li···lp } where *p* is the number of the pixels in the image and li ∈{0,1} . Thus, the set L is divided into 2 parts and the pixels labeled with 1 belong to object while others are grouped into background. The energy function is defined as following equation [4]

$$E(L)=\alpha R(L)+B(L) \quad (8)$$

Where, R(L) is called regional term which incorporates the regional information into the segmentation and B(L) is called boundary term which incorporates the boundary constraint into segmentation,α is the relative importance factor between regional and boundary term. When α is set to be 0, it means that the regional information is ignored and only considering the boundary information. In the energy function in eq. (8), the regional term is defined as following equation[4].

$$R(L) = \sum_{p \in P} R_p(l_p) \quad \textbf{(9)}$$

Where, Rp(lp) is the penalty for assigning the label lp to pixel p. The weight of Rp(lp) can be obtained by comparing the intensity of pixel *p* with the given histogram (intensity model) of the object and background. The weight of the t-links is defined as following equations [4]

$$Rp(1)=-\ln Pr(Ip|'obj') \quad (10)$$
$$Rp(0)=-\ln Pr(Ip|'bkg') \quad (11)$$

From eq. (4) and (5), we can see that when Pr(Ip|'obj') is larger than Pr(Ip|'bkg'), Rp(1) will be smaller than Rp(0) . This means when the pixel is more likely to be the object, the penalty for grouping that pixel into object should be smaller which can reduce the energy in eq. (8). Thus, when all of the pixels have been correctly separated into two subsets, the regional term would be minimized. B(L) In eq. (8) is the boundary term which is defined as following equation [4]

$$B(L) = \sum_{\{p,q\} \in N} B_{<p,q>} \cdot \delta(l_p, l_q) \quad (12)$$

Where p, q is neighboring pixels and δ(lp,lq*)* is defined as:

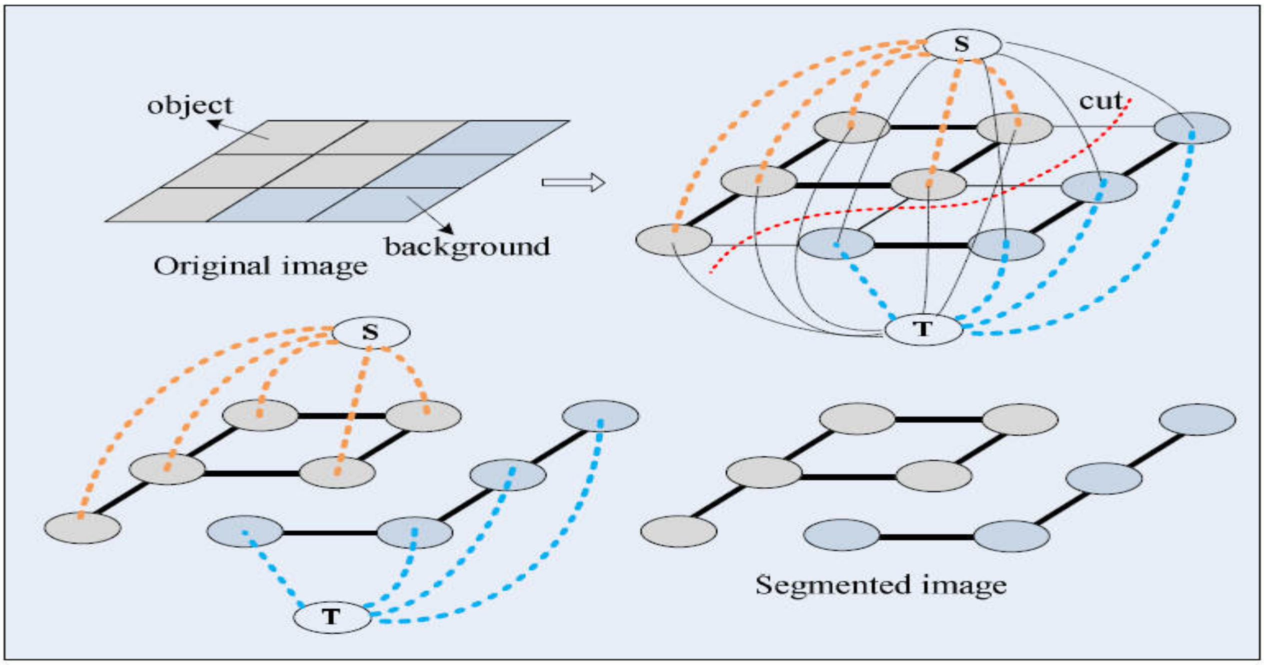

Figure 3.6.1 Illustration of graph cut for image segmentation.The cut is corresponding to the minimal energy of eq. (2)

$$\delta(l_p,l_q)=\begin{cases}1 & if\ l_p=l_q\\ 0 & if\ l_p\neq l_q\end{cases}$$

(12)

For the regional constraint, it can be interpreted as assigning labels lp,lq to neighboring pixels. When the neighboring pixels have the same labels, the penalty is 0 which means the regional term would only sum the penalty at the segmented boundary. For the term B<p,q > , it is defined to be a non - increasing function of $|Ip - Iq|$ as follows [4]

$$B_{<p,q>|} \propto \exp(-\frac{(I_p - I_q)^2}{2\sigma^2})$$

(14)

where σ can be viewed as camera noise. When the intensity of two neighboring pixel is very similar, the penalty is very high. Otherwise, it is low. Thus, when the energy function obtains minimum value, it is more likely occurred at the object boundary.

The weight of the s-t graph is given as following[4].

$$weight=\begin{cases}B_{<p,q>} & \{p,q\}\in Neighboring\ pixel\\ \alpha\cdot R_p(0) & for\ edge\ \{p,S\}\\ \alpha\cdot R_p(1) & for\ edge\ \{p,T\}\end{cases}$$

(15)

Eq. (15) can also be explained as that, in the s-t graph, when the intensity of the pixel is inclined to be the object, the weight between this pixel and s-node will be larger than that between pixel and t-node which means the cut is more likely occurred at the edge with smaller weight.

For the neighboring pixels, when their intensity is very similar, the weight is very big which is not likely to be separated by the cut. Thus, when the minimum cut is achieved from the s-t graph, the location of the cut is close to the object boundary. The implementation of the graph cut can be fulfilled by the max-flow/min-cut. In Figure 3.6.1 [4] illustrate the graph cut for 3×3 image segmentation.

III. EXPERIMENTAL RESULTS & DISCUSSION

A. EXPERIMENTAL SETUP

The data of chest CT images is used to evaluate the performance of the proposed algorithm are collected from the various websites. The format of the data images are various sizes like 190*200,271*186 and etc. This project implemented in MATLAB R2013a and supported system is Intel® Pentium® CPU A1018@2.10GHZ,2GBRAM. In the experiments, investigate the effect of performance on the following aspects.

B. THE EFFECT OF NUMBER K OF GMM

Shuangfeng et al. [1] .has proposed the Graph Cut algorithm using the GMM optimization for color image segmentation, and proved

Figure 4.3.1 shows the result of proposed algorithm.

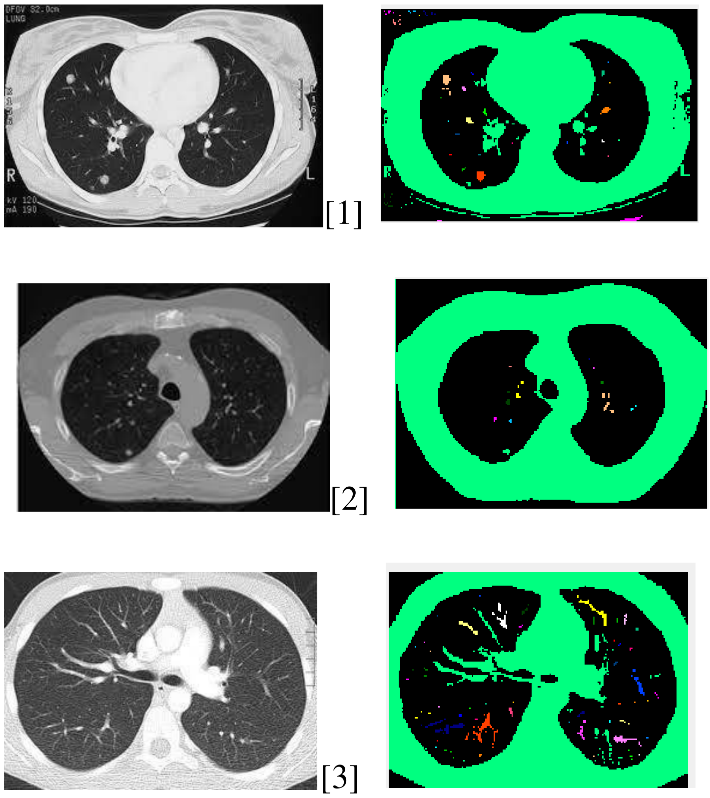

Figure 4.3.1 Original image (left), segmented result (right)

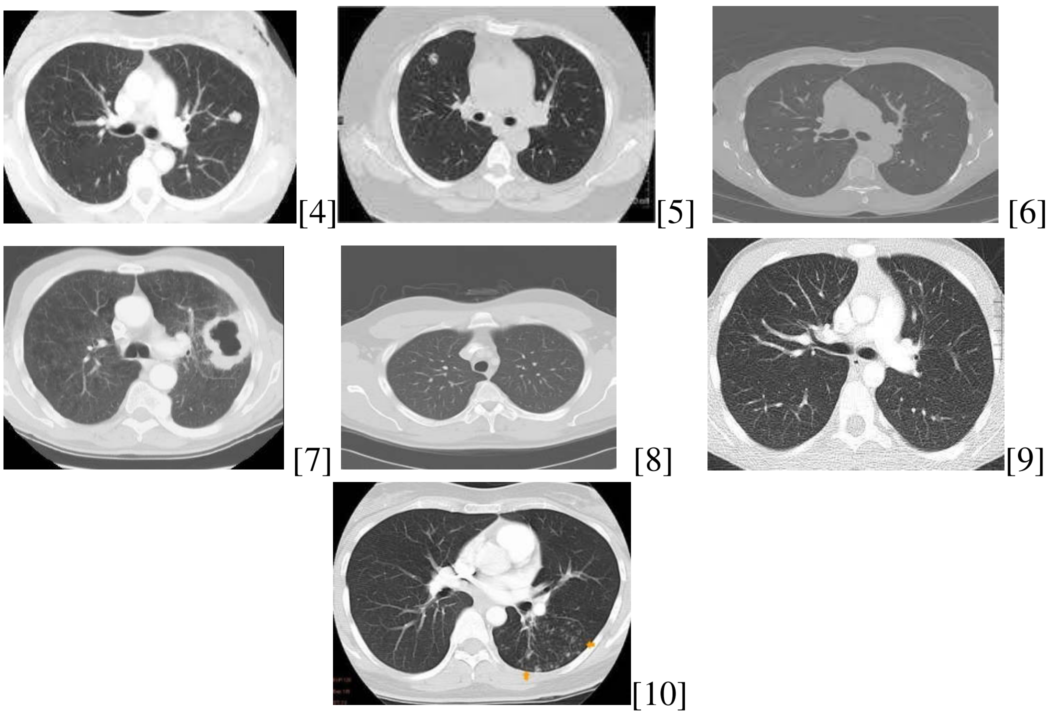

Figure 4.3.2 Input CT images[1]-[10]

segmentation to be accurate for Gaussian mixture number K>=5 and optimal for K=7.For my lung segmentation task, after tests on some data, Determined the time consumed for segmentation is higher if K is higher[1], so this project Choose K=3 in experiment. Refer fig.4.3.1

C. QUANTITATIVE EVALUATION

To evaluate the performance of the segmentation approach, Use only TPR (True Positive Rate) & FPR (False Positive Rate). TPR is the proportion of positive cases that were correctly identified (16). The FPR is the proportion of Negatives cases that were incorrectly classified as positive (17). Then find out the accuracy of segmented image.

$$TPR=TP/TP+FN \qquad (16)$$

$$FPR=FP/FP+TN \qquad (17)$$

Where TP is True Positive, FP is False Positive, FN is False Negative, TN is True Negative.

4.3.2 images segmented result is shows in following table 4.3.2

Image	TPR	FPR	ACCURACY
1	**0.15985**	**0.0061402**	**62.8605**
2	**0.12114**	**0.0053575**	**86.6558**
3	**0.13567**	**0.0005845**	**76.2678**
4	**0.22267**	**0.0067576**	**47.9812**
5	**0.14458**	**0.0058955**	**78.4797**
6	**0.18005**	**0.00562**	**77.9361**
7	**0.16307**	**0.0065517**	**52.6324**
8	**0.15501**	**0.0059029**	**69.4095**
9	**0.14306**	**0.0051849**	**71.8459**
10	**012519**	**0.0045916**	**82.5981**

IV. CONCLUSION

The importance of lung segmentation in lung CT image processing and the clinical analysis of lung disease, research on lung segmentation has received much attention in the past and many segmentation algorithms have been proposed. To facilitate the computer-aided lung lesion treatment planning and quantitative assessment of lung cancer treatment response ,and robust lung segmentation method is also needed. The graph cut algorithm has achieved spectacular progress in computer vision and image processing field, which inspires us to investigate its power in lung segmentation of CT images. In this work, a new method based on graph cut algorithm improved with GMMs is developed. The experimental results showed that the proposed method can directly provide explicit lung segmentation without any post-processing such as morphological operation. The accuracy of the CT images is approximately 75%, the segmentation accuracy and efficiency is significantly improved. All the cost mainly focuses on GMMs training process, the construction of corresponding graph and solving of the minimum-cut algorithm.

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