Lung CT segmentation for image retrieval using the Insight Toolkit (ITK)

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***Abstract*— Visual information retrieval is an emerging domain in the medical field as it has been in computer vision for more than ten years. It has the potential to help better managing the rising amount of visual medical data currently produced. One of the proven application fields for content–based medical image retrieval as diagnostic aid is the retrieval of lung CTs. The diagnostics of these images depend strongly on the texture of lung tissue and automatic analysis can be a valuable help.**

This article describes an algorithm to separate the lung tissue from the rest of the image to reduce the amount of data that needs to be analysed for content–based retrieval and focus the analysis to the really important part of the visual data. Most current solutions either use manual outlining for analysis or index the entire image without making a difference between lung and other tissue or background. As visual retrieval is usually applied to large amounts of data, our goal is to have a fully automatic algorithm for segmenting the lung tissue, and to separate the two lung sides as well. The database used for evaluation is taken from a radiology teaching file called *casimage* and the retrieval component is an open source image retrieval engine called *medGIFT*. Our current evaluation shows that the applied segmentation algorithm works on a large number of different cases and executes automatic segmentations for various data formats (DICOM, JPEG, ...). Segmentation quality does not need to be perfect around the outline. For image retrieval it is rather important not to miss any important parts of lung tissue. A small number of pixels from surrounding tissue are no problem. Difficult cases and workarounds are presented in the article.

I. Introduction

Content–based visual information retrieval has been an extremely active research area in the computer vision and image processing domains [1]. A large number of systems has been developed, mostly research prototypes but also commercial systems such as IBM's QBIC [2]. Main reason for the development of these systems is the ever–growing amount of visual data being produced in many fields, for example with the availability of digital consumer cameras at low prices, but also with the possibility to distribute data via the Internet.

The medical field is no exception and a rising amount visual data is being produced [3]. The radiology department of the university hospitals of Geneva alone produces currently more than $25,000$ images per day. The importance of retrieval of medical images was identified early [4, 5] and a large number of projects has started [6] to index various kinds of medical images. Not all projects are analysing the visual image content, many simply use the accompanying textual information [7]. This is often called content–based retrieval but should rather be called context–based retrieval as the text describes the context in which the image was taken. Very few projects are currently used in clinical routine. Most projects are developed as research prototypes without a direct link to a need in a clinical application.

Lung images have been analysed in the form of Thorax radiographs for computer–aided diagnostics [8]. Most retrieval projects concentrate on CTs of the lung. A fairly simple approach is given in [9] analysing the lung tissue in fixed sized blocks. A more sophisticated approach is used for the ASSERT system [10, 11]. A database with selected slices and regions marked by hand was used. This approach needs much expensive manpower but led to some proper results. For using the system, an MD had to submit a selected slice of a series and mark the important region in the image. Even a real user test was performed with ASSERT as diagnostic aid [12]. An improvement in diagnostic quality was reached using the system, especially for less experienced MDs. The performance of experienced radiologists was unchanged.

Our goal was to make the process of retrieval less labour–intensive for the generation of the databases and for the query process. The lung tissue was to be separated from the rest of the image, and only the lung tissue was supposed to be stored and analysed for retrieval. For the segmentation, an open source (OS) image analysis tool is used, *insight toolkit* (*itk*[1]), which is frequently applied for the segmentation of medical images. The retrieval engine is called *medGIFT*[2], based on the GNU Image Finding Tool[3]. The use of OS software facilitates the distribution of research results and sharing of resources among research groups.

II. Segmenting lung CTs

Segmentation is a main domain of medical image processing. It is often important to separate regions or objects of interest from other parts of the image. Mostly, segmentation is semi–automatic and a seed point is needed. Then, the structure is being segmented as exactly as possible, for example to measure its size, volume or form, in the case of a tumour. For us, the goal is not to have a perfect segmentation but an algorithm that does not need manual intervention. Goal is to quickly generate large example databases. It was not necessary

[1] `http://www.itk.org/`
[2] `http://www.sim.hcuge.ch/medgift/`
[3] `http://www.gnu.org/software/gift/`

to analyse all slices for 3D segmentation as our case database contains only selected slices that represent a certain pathology. On the other hand, there was no possibility to use information of connected slices to enhance segmentation. Lung image segmentation has also been applied to Thorax radiographies [13] but this seems to be a harder problem since lung borders are fuzzier and the projection contains ribs and several levels of other tissue. Segmentation algorithms for lung CTs in the literature are mostly pixel–based methods [14–20]. Some work has been done on knowledge–based segmentation [21, 22] taking into account a–priory knowledge on the structure of the lungs.

In pixel–based methods, the first idea is to eliminate fat tissue and bones. As the lung parenchyma has a very low–density, it is composed of low–intensity pixels in the CT scan. This property is exploited to separate the two lungs from the surrounding tissue. Generally, the image is thresholded, either at a fixed value [15, 16, 19, 23] or based on a computed threshold [14, 18, 20, 24]. A study from Kemerink [25] investigates the influence of the threshold and shows that a threshold of –400 Hounsfield units (HU) delivers good results.

As the air around the body has a very similar intensity to the lungs it will not be discarded by the thresholding, so it has to be removed. Either it is removed before the thresholding [14, 17, 20, 24] or afterwards [15, 16, 18, 23, 26]. Further steps are performed to improve the result. Parasitical objects that remain are removed and holes inside the lungs are filled. Several techniques are used for segmentation such as mathematical morphology [23, 26] and connected component analysis [15, 16, 18, 20, 23]. Another major improvement is the correction of the borders of the parenchyma. This is necessary when a nodule touches the border, which can lead to a bend in the contour. Such a correction is done by analysing the local curvature of every point of the contour [16, 19], applying a "rolling–ball" operator [14, 23] or mathematical morphology [18]. Gurcan *et al.* [17] developed a technique that compares, for each set of points in the border, the distance between them along the contour and along the line that connects them. Some studies identify the left and right side of the lungs. If the two lungs were merged in a previous step or because the tissues touch, they can be separated [15, 18, 20].

A. itk

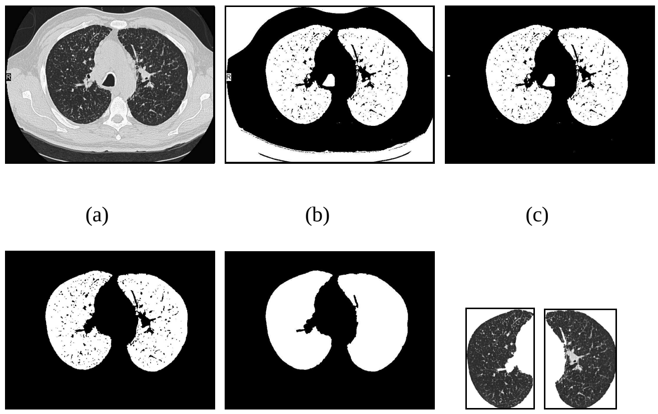
itk is an open–source (OS) software system for medical image segmentation and registration. It has been developed since 1999 on the initiative of the US National Library of Medicine (NLM) of the National Institutes of Health (NIH). As an OS project, *itk* is used, debugged, maintained and upgraded by developers around the world. It can be downloaded from the *itk* web page *itk* is composed of a large collection of functions and algorithms designed for medical image segmentation and registration. As the library is implemented in C++ it can be used on most platforms such as Linux, Mac OS and Windows. The decision to use *itk* was taken due to the quantity of segmentation tools it offers and the amount of research done based on it [27]. This allows us to concentrate on integrating tools rather than reprogramming and reinventing them.

B. Lung segmentation algorithm for image retrieval

Our lung segmentation algorithm follows these five steps:

1) The image is thresholded to separate low–density tissue (eg. lungs) from fat.
2) The surrounding air, identified as low–density tissue, is removed.
3) Cleaning is performed to remove noise and airways.
4) A rolling–ball operator is used to rebuild lung borders.
5) Finally, the left and right lungs are identified and separated if needed.

Figure 1 illustrates the original image and steps of the segmentation process.



(a) (b) (c) (d) (e) (f)

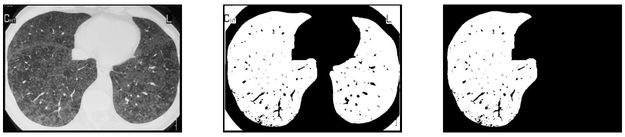
Fig. 1. Segmentation steps: (a) Original, (b) thresholding, (c) background removal, (d) airway and noise removal, (e) rolling–ball operator, (f) left, right lung separated.

1) Optimal thresholding: The first step is thresholding the image. A thoracic CT contains two main groups of pixels: 1) high–intensity pixels located in the body (*body* pixels), and 2) low–intensity pixels that are in the lung and the surrounding air (*non–body* pixels). Due to the large difference in intensity between these two groups, thresholding leads to a good separation. Since our algorithm needs to handle JPEG as well as DICOM files, the fixed threshold of –400 HU proposed by Kemerink [25] is not applicable. The method applied is the *Optimal Thresholding* defined by Hu *et al.* in [18]. This iterative procedure computes the value of a threshold so that the two groups of pixels are well separated. It works as follows: Let T^i be the threshold value at step i and μ_b, μ_n be the average intensity value of *body* pixels (*i.e.* with intensity higher than T^i), respectively *non–body* pixels (intensity lower than T^i). The threshold for step $i+1$ is:

$$T^{i+1} = \frac{\mu_b + \mu_n}{2}.$$

This procedure is repeated until convergence, *i.e.* until step c where $T^c = T^{c-1}$. The initial threshold T^0 is set to 128 which is the median gray level. When convergence is reached, the image is thresholded at value T^c. Every pixel with an intensity higher than T^c is set to 0 (*body* pixels) and the others pixels are set to 1 (*non–body* pixels).

2) Background removal: The air around the body (background) is removed using an idea from [18, 26]. Background pixels are identified as follow: they are *non–body* pixels and connected to the borders of the image. Thus, every connected region of *non–body* pixel that touches the border is considered as background and discarded. Problems with this background removal technique appear when one of the lungs touches the border of the image. It appears if the CT scan was cropped too close to the lungs, which is common in our teaching file. In this case, the lung that touches the border will be removed as if it was a part of the background as can be seen in Figure 2.



(a) Original image (b) Thresholding step (c) Background removal

Fig. 2. The right lung touching the border is removed with the background

3) Cleaning: Once the background is removed, several *non–body* regions remain. Airways are sometimes found in these regions such as the trachea or the bronchi. Since the airways are empty cavities, the intensity of pixels in the area is low. To remove these regions, an area with an average intensity lower than $T^c/2$ (T^c is the threshold used previously) is searched for. Then, *non–body* regions smaller than 20 pixels are removed, which eliminates noise that could interfere with the rolling–ball in the following step. The airway removal can pose problems when parts of the lung have a very low density. If those parts were separated from the rest by thresholding, they can be interpreted as airways (shown in Figure 3).

(a) Original image (b) After cleaning

Fig. 3. Part of the left lung was removed with the airways.

4) Rolling–ball operator: Rarely, holes can appear near the border of the parenchyma. The parenchyma can then be divided into several parts by the thresholding. To fill theses holes and glue different parts of a same lung half together, a rolling–ball operator is applied to non–body pixels [14, 23]. The rolling–ball operator is in fact a morphological closing of the region followed by hole–filling. The structuring element is a disc with a radius of 2 pixels. This radius was chosen for its ability to glue enough parenchyma tissue of the same lung together without influencing other regions (eg the other lung). Despite the small disc size, very close lungs can be merged due to the rolling–ball. These kind of cases need to be managed in the separation step that follows.

5) Left/right lung identification and separation: Finally, the two lungs are identified and separated. If the number of connected components is higher than one, each region is attributed to the left or the right lung depending on whether its centre of mass is in the left or right half of the image. Like this, cases of lungs that were cut into several parts can be handled. If there is only one connected component (two lungs are connected), they are split into two regions. Due to our application of this segmentation for image retrieval, there is no need for a perfect separation. The region is simply cut vertically in the middle.

As we use a teaching file, some images were cropped to show only one lung containing the main pathology. In this case, only one connected component is identified and has to stay intact. A condition was added for separation. This rule is based on the shape of the bounding box: if the ratio height on width is bigger than 0.8 (nearly square to vertical rectangle) the region is considered as one lung and not cut in two. Otherwise, the region is considered as two merged lungs and they are separated.

C. *Implementation with* itk

One of *itk*'s extremely useful features are image iterators. The iterators allow to traverse every pixel of an image or a portion of an image quickly to apply any treatment such as pixel count, average gray level of a region, etc. This was used frequently. Specific tools were employed for the 5 steps of the algorithm. The optimal thresholding is realised using a `BinaryThresholdImageFilter` at each step. Connected regions can be found applying a `NeighborhoodConnectedImageFilter` on a seed point: for the background removal, every white pixel of the border of the image was used as a seed point. The rolling–ball operator was simulated with a closing operation followed by a hole–filling step. The closing operator is employed by applying two filters: `BinaryDilateImageFilter` and `BinaryErodeImageFilter`, using a `BinaryBall-StructuringElement` with radius 2 pixels.

III. THE RETRIEVAL COMPONENT

A. casImage

The radiology teaching file that serves as a base for our system is called *casImage*[4], an in–house development of the university hospitals of Geneva [28]. Currently, more than 60,000 images are stored in the system. A database with 9,000

[4] `http://www.casimage.com/`

images is freely accessible on the web, compatible to RSNA MIRC[5] (Medical Imaging Resource Centre). Images can be added to the system directly from radiology workstations, making it well accepted among clinicians. Around 500 images are added per week. On the insertion of an image into the database the level/window settings are fixed. Images are stored in JPEG and thumbnails are created to be shown on screen. This means that we do not have the full resolution of grey scales available. Our algorithm was created to work with either the DICOM images or with JPEG images from *casImage*.

B. medGIFT

The GNU Image Finding tool (*GIFT*) is the outcome of the *Viper* project of the University of Geneva [29]. *medGIFT* is an adaptation of *GIFT* [3] adding a new interface and experimenting with feature sets. The number of grey levels and importance of texture are different in medical images than photographs. *GIFT* uses techniques well known from text retrieval for the indexing of images such as frequency–based feature weights, inverted files for efficient data access and simple relevance feedback. The four feature groups currently used are:

- a global colour and grey level histogram;
- local colour blocks at different scales and various fixed regions;
- a global Gabor filter response histogram using several scales and directions;
- local Gabor blocks in fixed areas of the image in several scales and directions.

IV. RESULTS

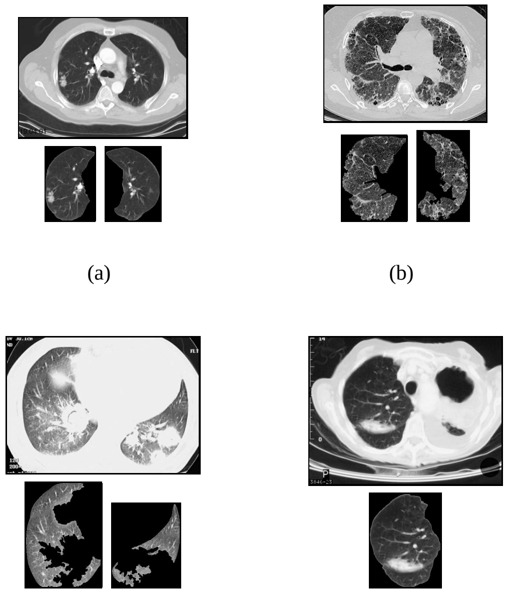
A. Segmentation results

Fig. 4. Interface for the evaluation of the segmentation quality.

To evaluate the accuracy of the algorithm a collection of 153 lung CTs was extracted from the *casimage* database and segmented. Then, each input image and the resulting segmentation was evaluated for quality. To make this task easier, a simple interface was built (Figure 4). This interface presents each image and its segmentation. It allows the user to classify the segmentation quality:

(a) The segmentation is good, all lung tissue is taken.
(b) A small, insignificant part of the lungs is missing.
(c) Larger parts of the lungs are missed or fractured.
(d) The segmentation delivers bad results.
(e) The segmentation is bad, because the CT image is not at all standard.

Examples of the first four classes of regular images are shown in Figure 5. Twelve images are in class 5. 5 of them are shown in Figure 6: the logo of the hospital figured on a CT scan 6(a). Unfortunately, it is a black box and touches border and right lung which is removed with the background. 6(b) shows a cropped scan. The right lung touches the border and is removed with the background. Such a case does not appear in clinical routine. Figure 6(c) was annotated with coloured flashes, creating an artifact on the segmented lung. Figure 6(d) shows an image taken sideways. Our method is not able to determine the side of each lung. Both lungs where classified left because both mass centres are on the left side. In Figure 6(e), background parts were too big and considered as lung parts. These twelve non-standard images were removed from the collection for further evaluation. Of the 141 remaining images, 59 were well segmented (Figure 7), small parts were missing in 57 images, big holes were visible in 32 images and 3 images were badly segmented.

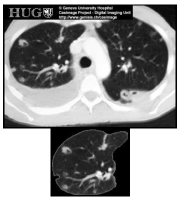


(a) (b) (c) (d)

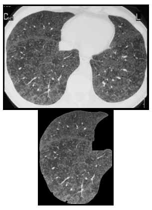
Fig. 5. First four classes: (a) good segmentation, (b) small parts missing, (c) large parts missing or fractured, (d) segmentation failed (right lung missing in this case).

For our goal of image indexing and retrieval, segmentation does not need to be perfect. If small parts are missing, feature

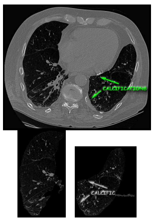
[5]http://mirc.rsna.org/



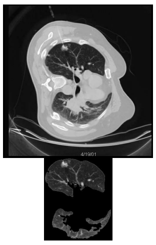
(a)



(b)



(c)



(d)

(e)

Fig. 6. Some unusual cases.

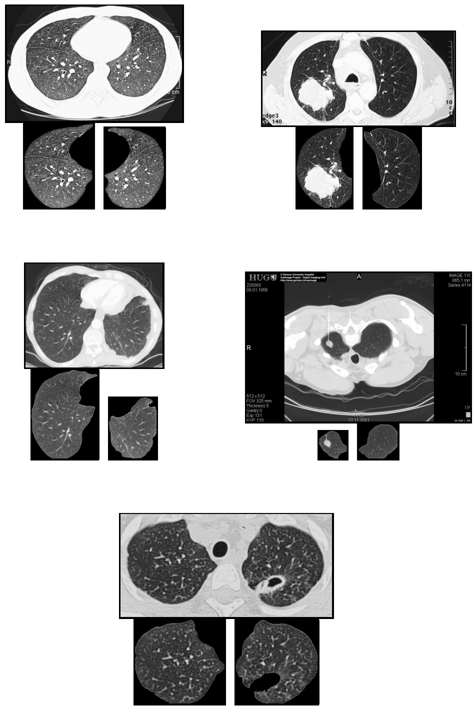


Fig. 7. Satisfying segmentation.

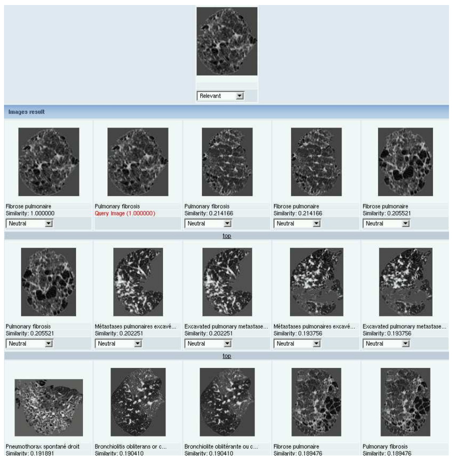


Fig. 8. Example of a query result using *medGIFT*.

extraction will not be extremely different. It is not important, either whether two lungs were perfectly separated. For these reasons, the two first categories of well and quite-well segmented images were considered as being of sufficient quality, the rest was considered as unsatisfying segmentation. With these criteria, 116 images were sufficiently well segmented and 35 images delivered unsatisfying results. This leads to a rate of 82.3% for sufficient segmentation.

B. *Retrieval results*

So far, only a prototype of the retrieval engine is used that analyses the entire image with grey level and texture measures as explained in Section III-B. The mode colour was taken to fill the area around the parenchyma so the Gabor filter responses are not altered by a large grey level change on the borders. Diagnoses of the images are shown as text under the images to allow for a quick visual evaluation. No quantitative evaluation of retrieval performance has been performed, yet. Figure 8 shows our visual retrieval interface with a query result using a single input image. User feedback can be given with several relevant and irrelevant images to refine the search.

V. CONCLUSIONS AND FUTURE WORK

This article shows a simple segmentation algorithm for lung CT images. Obtained segments can be used for content–based image retrieval as a diagnostic aid. An evaluation of the segmentation quality shows good results. First qualitative results for lung image retrieval show that the visual retrieval is much better than when taking into account the entire image. All tools used are based on OS programs and the source code can be obtained from the authors. The segmentation algorithm proves to be simple but effective for our purpose. Several abnormal cases were included into the algorithm and allow for a reliable segmentation of the lung tissue and a separation from surrounding background. This allows to focus the retrieval on the really important parts of the image.

Currently, our retrieval algorithm is not perfectly adapted to the obtained images. As the segmented lung parts are entirely indexed, the edge between the segmented regions and the background results in strong responses of the Gabor filters. This means that the form of the lung parts becomes important as well whereas the actual tissue texture should be the most important. Besides a concentration of feature extraction on the parenchyma, the main future work is on validating the quality of the algorithm with clinical data and especially with images using DICOM and the full range of grey levels. Currently an annotated image database is being created for this evaluation.

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