LUNG SEGMENTATION USING 3D REGION GROWING

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ABSTRACT

Lung cancer is one of the most common and serious types of cancer. Lung segmentation is a vital first step in radiologic pulmonary image analysis and lung lesions detection. In this project, we proposed a method that performs lung segmentation using a combination of contrast enhancement, 3D region growing, watershed and other morphological operations. The result of our method is very robust. Despite having heterogeneous images in the dataset, we managed to get a Jaccard Index of 0.968 averaged over all patients in the dataset available from *Vessel12 Grand Challenge*.

Index Terms— Lung Segmentation, 3D Region Growing, Watershed, CT scan

1. INTRODUCTION

Lung cancer, also known as lung carcinoma, is a malignant lung tumor characterized by uncontrolled cell growth in tissues of the lung. When unidentified for a long period of time, it can have adverse effects and can lead to death of a patient. Therefore, early diagnosis is extremely important.[5]

Computed Tomography (CT) is an important diagnostic modality used in the medical domain. Since CT images are digitized, it is vital to use advanced image processing techniques to aid in any sort of analysis, reconstruction, etc.

The aim of medical image segmentation is to extract quantitative information (e.g. volumetric data, morphometric data, textural patterns related information) with regard to an organ of interest or a lesion within the organ. In general, a segmentation problem can be considered as consisting of two related tasks: object recognition and object delineation. Object recognition is the determination of the target objects whereabouts on the image or its location, whereas object delineation draws the objects spatial extent and composition.

Although object recognition is known as a high-level process, object delineation refers to a low-level process; and it is well known that humans are superior to computers at performing high-level vision tasks such as object recognition. On the other hand, computational methods are better for low-level tasks such as object delineation and finding the exact spatial extent of the object.

Thus, in this paper, we propose an object delineation method for segmentation of the lung taking a three dimensional approach using techniques such as region growing and watershed among others, which are unsupervised techniques.

2. MATERIALS

The publicly available dataset from the *Vessel12 Grand Challenge*[7] which was used during the development of our solution is a 3D .raw format image with .mhd header file. We used in the Insight Segmentation and Registration Toolkit[1] library to read and visualize the images.

It should be noted that in our proposed solution, due to the use of 3D region growing, we have used the SITK library[2, 3, 4] since it has an abundance of algorithms that perform well with three dimensional data. It takes into account additional factors when compared to two dimensional algorithms such as spacial information. In addition, we used Open-CV functions during pre-processing and post-processing stage of our pipeline like small hole filling and morphological operations among others. Thus usage of both SITK and Open-CV packages have help improve results.

3. METHODS

The approach we have developed consists of six basic stages. The first stage in our pipeline, as shown in the figure 1, is the pre-processing step that is performed to ensure there is similar contrast among the patient images.

As stated above, the images had varying intensity distributions that needed to be generalized to make the processing much easier and effective. Most of the images had a normal range of intensities(between -1000 to +1000) but some of the patient images had a wide range intensities from -6000 to +4000. Those images with intensities at the lower extremes were the ones with a hazy overlay of grayness. To enhance the contrast of the images with extreme intensity values, we found out that intensity clipping works. The intensities values lower than -1000 were clipped and replaced with -1000 and those greater than +1000 were replaced with +1000. This brought all the images to have similar contrasts and intensity distributions.

After contrast enhancement, all images are normalized in a range of 0 - 255 because most of the image processing functions in OPENCV and other libraries do not accept negative intensity values.

Following pre-processing, the next stage is segmentation. The approach chosen for this task is a 3D region growing algorithm, a *simpleITK* function called *NeighborhoodConnected*. It is similar to 2D region growing in which you select a seed, pixel or group pixels in which a region starts growing. The main difference is in 3D, region grows in volume. In our case, we used two seeds for each lung cavity. As predicate, we used a neighbourhood size of 8-connected pixels and we selected an appropriate intensity range in which the region can grow. Therefore, the 8 connected pixels will only be included if they have intensities that fit within the given intensity range. The minimum intensity is the lowest possible intensity value (i.e. 0) and the maximum intensity level is obtained by applying a Otsu's thresholding, that will help differentiate the dark regions of the lung from the rest of the CT scan.

In order to perform region growing of *Neighborhood Connected*, it is important to find seed that is present within the cavity of the lung. Finding the right seed is critical, since a pre-fixed seed value will fail for many cases. Therefore, an automated approach must be developed to find one based on the case at hand. The seed selection algorithm that we implemented is based on finding a binary image with a roughly found mask of the lung cavity, and locating the geometric center of the object (i.e. the lungs). If the lungs are disjoint, the center of either lung cavity can be used as the seed. In case the lungs are attached, finding the geometric center of the lung cavity will result in a point outside the lung cavity that is between the lungs. Thus, a method to identify this case has been implemented which finds the area of the objects in the roughly found masks. If the area is really large, we know that both lungs are joined, and thus we use a different approach to find the seed in this scenario.

In 3D region growing, removing the trachea is challenging because it is connected to the lungs via bronchi. As a solution, we used 2D watershed segmentation on each slices of the 3D image.

The input image of watershed is a binary image (output of 3D region growing). First, we automatically determine an internal marker for both lungs and trachea using local maxima of distance transform. The distance transform calculates the euclidean distance between foreground pixel and the nearest background pixel. The maxima of this distance are chosen as internal markers. As we know, trachea is located between the two lungs which is in the middle of the image. So, we removed the markers (seeds) which are found in the middle. Since we know the location of the pre-selected seeds, flooding only happens within the lung cavity. Additionally, we applied the watershed only on the slices containing trachea.

After removing the trachea, there are a lot of holes generated because of the tissues found in the lungs. To fill those holes, we should first extract them by computing the difference between the filled lung and the watershed results. Once this is done, we have to find the contours of the holes and select those whose area is smaller than a threshold in order to avoid the selection of the cancer tissues.

Finally, after filling holes, there are some gaps within the lungs which can not be filled by the method used above. Therefore, we used morphological operations more specif-

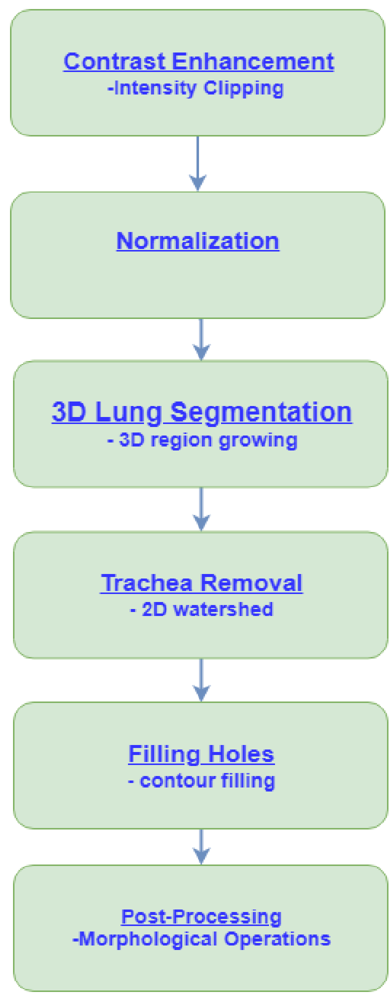

Fig. 1: Methods used for Lung Segmentation

ically successive dilation and erosion using different sized structuring element.This method helped us to improve the accuracy of the final result.

4. RESULT AND DISCUSSION

4.1. Result

After applying the methods mentioned above, the result of each step is depicted in the figure 2.

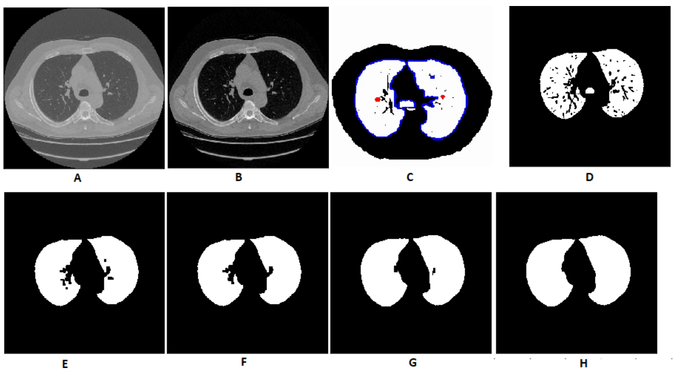

Fig. 2: Image result after each processing pipeline: A) Original Image, B) Contrast Enhancement, C) Seed Selection D) 3D region growing E) Watershed F) Filling holes G) Post-processing(Final Result) H) Ground Truth

To evaluate the performance of our segmentation method, we used Jaccard Index, which computes intersection of the output image and the groundtruth divided by their union.

$$JaccardIndex = \frac{tp}{tp + fp + fn}$$

tp: when pixels are $\neq 0$ in the output and in the groundtruth
fp: when pixels are $\neq 0$ in the output and $= 0$ in the groundtruth
fn: when pixels are $= 0$ in the output and $\neq 0$ in the groundtruth[6]

After running our proposed segmentation method in all the patients, we get an average Jaccard Index of 0.968, which is near to the state of the art's Jaccard Index of 0.98.

Here is the Jaccard index of each patient images in the dataset:

4.2. Discussion

It is important to note that there were a few key steps that really helped us to achieve the results mentioned above. The first was the pre-processing that provided similar images, and second the automatic seed selection for each lung cavity. The

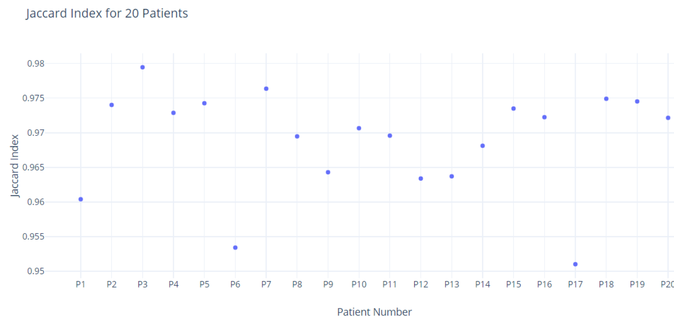

Fig. 3: Jaccard Index of 20 Patients from the dataset

reasoning behind selection of two seeds instead of one is due to the fact that in some cases, region growing goes to the outside of lungs. Thus using additional seed solved the problem.

Additionally, there are few challenges we faced due to the dataset available. One such challenge were scans not having similar image intensity distributions. About half the patients' scans have a gray/hazy overlay when compared to the others. To fix this, all images require a pre-processing step to ensure similarity between patient data. Another challenge faced was not due to bad image quality, but related to the patient whose scans were taken, such as one particular case (patient 13) where the trachea is connected to the outside world through a pipe, which was a challenge when using region growing. This is due to the fact that the neighboring pixels of the trachea and the outside region are now similar, resulting in the outside region being added to the grown region.

In some patients, there were cancerous regions in the lung that resulted in large holes in the binary masked image among other smaller holes resembling noise. Since this is followed by hole filling, we faced the challenge of somehow preventing the filling of the holes of the cancerous regions. We overcame this by taking into account the areas of the holes present and filling those that were less than a certain threshold area defined. We found this to be very effective and provided a small improvement in the results. In figure 3, we can see the distribution of how well our pipeline performs for all the patients.

5. CONCLUSION AND FUTURE WORKS

5.1. Conclusion

To conclude, we were able to successfully complete the segmentation of the dataset which have heterogeneous patient images, by applying 3D region growing algorithm which provides a performance boost since spatial information is being considered. We did face a few challenges but were able to come up with techniques to overcome them.

In our approach, the algorithm we developed is able to deal with the challenges posed by different patient data such as dealing with the presence of pipe and presence of cancer in lung.

5.2. Future Works

In the methodology we have taken, there are areas of improvement that we would like to experiment with further.

In some cases of hole filling, the small unwanted holes are clustered and connected resulting in a large area covered which tricks our hole filling algorithm into assuming it is a cancer and not filling them. We could develop a method to prevent this from happening by taking into consideration the shape or other features of the holes.

Another improvement we could work on is the removal of small regions of the bronchi being included in our segmentation. Since the intensities of the lung cavity and the bronchi are very close, being able to differentiate them could be an additional step that can be include in the future.

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