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# Automated lung segmentation on digital tomosynthesis images with complex method

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***Abstract* – For lung screening the most common method is chest radiography, which produces summation images without giving any depth information about the lung. Computed Tomography (CT) creates excellent slice images, which give volume data that makes CT a more sensitive nodule detection system. However CT has disadvantages, it is too expensive and it's x-ray emission is too high to be used as an everyday screening method. Digital tomosynthesis (DTS), as a relatively new chest imaging modality, can be positioned between chest radiography and CT. While it produces slice images of the chest similarly to CT, its slice thickness is larger, it creates a bit more blurred slices, it has much lower radiation than CT. This blurring makes it hard to segment the lung areas automatically, which is essential for an efficient Computer-aided Diagnosis system. The paper proposes a combined method, which starts from a previously published approach, extends it using snake methods and adjacent images' segmentation information to improve lung segmentation. Experiments show that the combination of methods reduces the incorrectly segmented lung region.**

***Keywords* – medical imaging, digital tomosynthesis, lung segmentation, computer-aided diagnosis.**

## I. INTRODUCTION

Lung cancer is one of the leading causes of death. Early detection of the lung nodules can increase the survival chance of the patient. The most common screening method used to inspect the lungs is chest radiography, which produces single summation images. These x-ray images do not give in-depth information about the lung, so abnormalities, like lung nodules cannot easily separated from other anatomical shadows like vessels, bones, etc. Although computer tomography (CT) is a much more sensitive imaging modality, its cost and the radiation dose a patient obtaining during a CT scan are obstacles of using it for large scale screening. These drawbacks are true even for its low dose version (LDCT). Chest digital tomosynthesis (DTS), as a relatively new imaging modality, can be positioned between chest radiography and CT [1]. While it produces (coronal) slice images of the chest similarly to CT, its slice thickness is larger, it creates a bit more blurred slices, the radiation dose produced during a DTS scan is much lower than that of a CT scan. A further consequence of using DTS is that instead of a single x-ray image a DTS scan produces about 100-400 coronal slice images. So reading the images of a complete scan needs more time and thoughtfulness from the radiologists/pulmonologists.

Computer-aided Diagnosis (CAD) can help physicians, can improve radiologists' efficiency as it detects nodule-like areas, helping radiologists to decide if this area can be regarded as a potential abnormality or not.

A modern CAD system has 3 main parts:

To create Regions of Interest (ROIs), robust methods are needed to segment the lungs from other parts of the image, to determine areas of the images where any abnormality are looked for. The second part is to find suspicious regions inside the previously segmented area. The third part is to classify the candidate nodules with machine learning tools and give a list of potential lesions which can be overlooked by doctors.

This paper focuses on the first step of the procedure, it proposes a complex lung segmentation method of DTS slice images. DTS is considered as a 2,5D imaging technique. It creates projections similarly to standard x-ray radiography, however instead of getting a single projection of a patient, 40-60 projections are taken from different angles. From these projections reconstruction algorithms are used to compute the coronal slice images of the chest. Because the projections are taken from a limited angle range, the coronal slices are not ideally thin, and there is some blurring between the neighboring slices too. Although the spatial resolution of the images is rather good (the coronal slices are at least 1000x1000-pixel images) their in-depth resolution is poor making difficult to obtain 3D information about the lung. Central slices have relatively high quality, but as going further from the central slice, images' quality is getting poorer, what can mislead the segmentation methods on non-central images. This paper proposes a complex segmentation procedure, which starts from a method published in [3], but as the result of this previous method does not seem satisfactory, further steps are introduced. The complex algorithm applies three different approaches: an intensity-based, a gradient-based and energy-based segmentation in order to make the algorithm more robust and accurate. The efficiency of the method is increased by combining information from the adjacent images.

This paper is organized as follows: Section II is a short summary of the previous results, it describes the most promising solutions and shows their deficiency. In Section III. the previous method's improvements are described. Evaluation is presented in section IV, where simulated DTS images are used, which are generated from CT images, to get at least acceptable standard reference lung contours.

## II. RELATED RESULTS IN THE LITERATURE

DTS is a relatively new medical imaging modality. Its main application is related to breast screening [4], while only a few products can be found where DTS is used for chest screening [5]. Such previous results that are dealing with computer aided detection or diagnostic (CAD) systems based on DTS are even fewer. According to the knowledge of the author there are only very few papers dealing with the problem of lung segmentation in chest DTS slice images. The paper of Seung-Hoon et al. [2] proposes segmentation using only intensity information with region growing method on central images. This paper recommends using a previously selected fixed pixel as an inner point, which is the initial point of the growing method. This approach is not considered as a robust method, because it is sensitive to position of the patient. It also suggests rolling-ball, where a ball shaped element is rolled along the edge of the segmented area to get smooth lung borders in the end, as a useful post-processing step.

Automated lung segmentation in chest DTS [3] uses the gradient information of the image and searches the lung masks along the edges by dynamic programming. The gradient image is transformed into polar coordinate system where an inner point determined previously is used as the origin of the polar coordinate system. This approach works quite well in the central slice images, as in these images the lung area has rather definite and sharp borders. This paper also proposes a method on how to handle non-central images. The basic idea is that the neighboring slices are rather similar, so the gradient images in these slices must be similar too. The results using these approaches are quite remarkable however the robustness of these methods should be improved. As the variability of DTS images obtained from different patients are rather large, the performance of these methods varies greatly.

A typical gradient image of a DTS slice is shown in Fig.1 and its version in the polar coordinate system is shown in Fig. 2. As it can be seen, there are a brighter and many pale paths in the image, and these paths are going through the gradient image near horizontally, as the lung contour, where there may be larger gradients, surrounds the inner point. In this unfolded image dynamic programming is used to find a route connecting the brightest points. The drawback of this algorithm is that it assumes that one column of this image belongs to one angle, that is only convex shapes can be identified using dynamic programming. A cost function is assigned to each pixel, which has 2 components, one of them is the intensity of the pixel, it is used as a reward, and the second component is the distance difference from the previous pixel, this is used as a penalty. More details about the cost function are available in the paper [3].

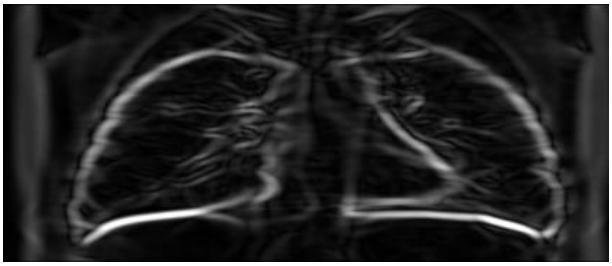

*Fig. 1. Gradient image of one DTS slice in Cartesian coordinate system, it is squeezed along vertical dimension to set each lung's width and height to similar size. This step is done in order to eliminate as much jump on the path as possible.*

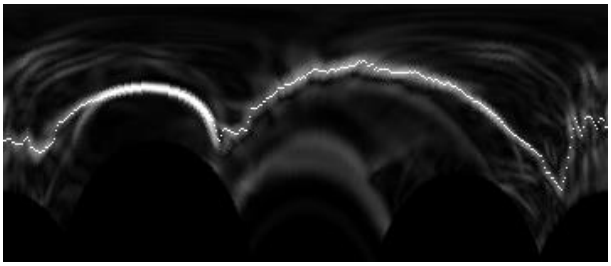

*Fig. 2. Gradient image of one DTS slice in polar coordinate system, white pixels marking the calculated path. Only right lung is shown in this image.*

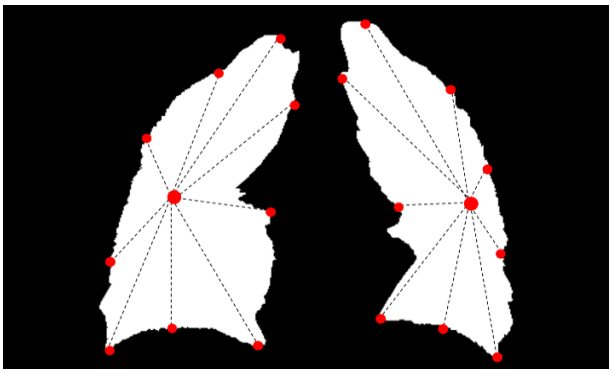

*Fig. 3. After reconstructing the found path, center of the lung and some point is highlighted with red dot.*

Concave segments may show up around the heart, so using this approach the area under the heart can't be segmented correctly, additional methods are required to find this region. There is another disadvantage of dynamic programming. Two paths can be very different while they may have similar costs. The consequence is that there may be very similar slice images, but the segmented masks can be significantly different what makes this method less robust.

This study [3] also suggests a method to reduce wrong segmentation on non-central slice images, by fading unlikely positions' pixels on the polar coordinate images, as the assigned positions on the adjacent slices must be close to each other. On the current gradient image the pixel values are multiplied by a Gaussian function, where pixel's distance from the adjacent image's selected point in that column is assigned as Gaussian function's variable.

$$I'(x,y) = I(x,y)G(O(x) - y) \quad (1)$$

Where $I(x,y)$ is the intensity value of one pixel of the polar coordinate image, at the $x$-th column and $y$-th row. $G$ is a Gaussian weighting function, and $O(x)$ is the neighboring image's row index in the gradient path, which image is towards the center slice. So $O(x)$-$y$ is a distance between the two selected pixels in the $x$-th column. Images are processed from the center slice towards the non-central slices.

This model eliminates problems in many cases, but sometimes a wrong central image could mislead the whole process. It is more desirable to have more images around the central one instead of exactly one, because a poorly chosen slice as a center image can reduce the accuracy. This is based on the assumption that, choosing such images where at least half of them considered as blurred ones is less likely.

An important and hard problem of lung border detection is to validate the results. The study [3] uses reference lung contours, which are created by radiologists. However the real lung contours in DTS slice images are very difficult to determine even for skilled radiologists. On the central slice images it is quite easy to determine the lung contour, but on non-central images expected lung area based only on DTS can hardly be determined. This is why more information is needed to get at least approximately correct lung borders on non-central images.

## III. DESCRIPTION OF THE METHOD

Using only pixel intensity values to determine lung area is impossible as -in contrary to the CT images- on the DTS images the intensity values are not standardized. This means that on DTS images an universal intensity limit, correct for differentiating lung area from non-lung areas on every image, cannot be identified. Instead picture-dependent limits should be defined. Below this limit all pixels are considered as part of the lung. The correct value of the intensity limit can be determined by using the histogram of the image. First the histogram is smoothed using a low pass filter to reduce noise and the effect of missing intensity values. A simple averaging filter with a 5-pixel kernel is used. The histogram has two valleys after filtering. A proper limit value in the smoothed histogram will be the local minimum of the first valley.

After that morphological methods are used to get continuous lungs and to remove noise. Experiments show that eroding with smaller structure and dilating with bigger structure gives the best results.

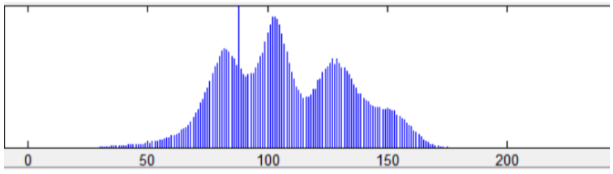


*Fig. 4. Original histogram of a chest tomosynthesis, some intensity values are missing.*

Next some inner point of each lung called center point must be determined. The image is split vertically at the center into 2 parts (the two (half) lungs), so one lung is processed by the method, then use this formulas, $P(x,y)$ is the value of binary mask at $(x,y)$ pixel:

$$Center_x = \sqrt{\sum_{(x,y)} x^2 P(x,y)} \quad (2)$$

$$Center_y = \sqrt{\sum_{(x,y)} y^2 P(x,y)} \quad (3)$$

Results show that this point isn't optimal, because it is near to the arteries and the heart, which can be misleading for the further steps of the method. The centers are translated to the outer side of the lung by 8% of the image width and translated upwards by 10% of the image height. (An example of the selected center points are shown in *Fig. 5*)

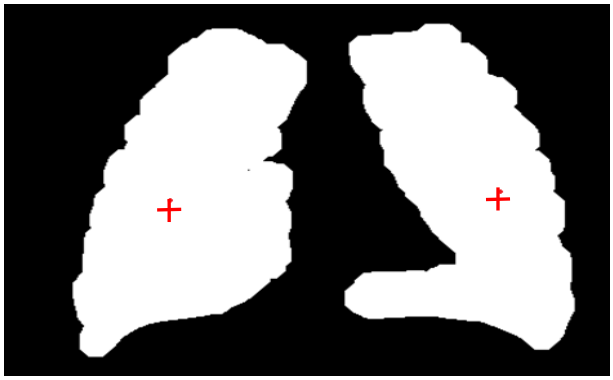

*Fig. 5. Segmented area based on pixel intensity, after morphological steps, red dots are the calculated centers.*

The next step is using a path finder algorithm. Due to previously mentioned problem of ambiguity of getting a path, additional smoothing is needed. Get every point of the lung contour on each slice and make a function from it, the values of the function will be the distances from the central point. Generate these functions ($F_x(y)$ belongs to the of $x$-th point of the boundary and $y$ is the index of the slice, as you can see on *Fig. 6.*), then convolve the function with a smoothing filter ($H$), so it decreases the big steps on the masks between the adjacent images.

After the convolution convert the values back to Cartesian coordinate system to get the suggested path.

$$F_x'(y)=F_x(y)*H \quad (4)$$

$$H=\frac{1}{5}[1\ 1\ 1\ 1\ 1] \quad (5)$$

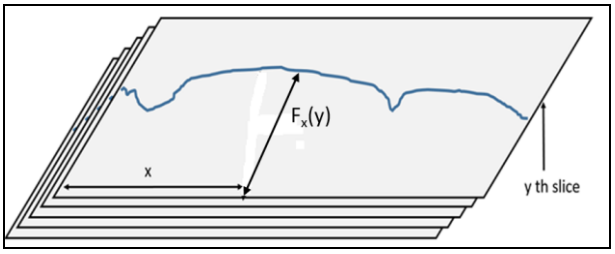


*Fig. 6. Construct $F_x(y)$ function based on images in polar coordinate*

In the end the presented method works almost perfectly on the outer side of the lung, but it gives rather bad results near the mediastinum.

Fortunately, there is a method that works better on the inner side of the organ: we can use active contour model (sometimes referred to as Snake) to find the region under the heart on left lung and it also works more or less on the mediastinum. Active contour model [6] is based on energy minimization, it creates smooth contours and, at the same time, it takes the edges into consideration. The energy formula is the sum of the smoothness of the contour, the continuity of the contour (first two components known as internal energy) and image energy. Furthermore, with correct parametrization, on images, that differ slightly it creates almost identical masks. It is an iterative method and needs an initial mask. An intensity-based segmentation is considered as a satisfying initial mask. It contains the region under the heart, but it isn't accurate enough.

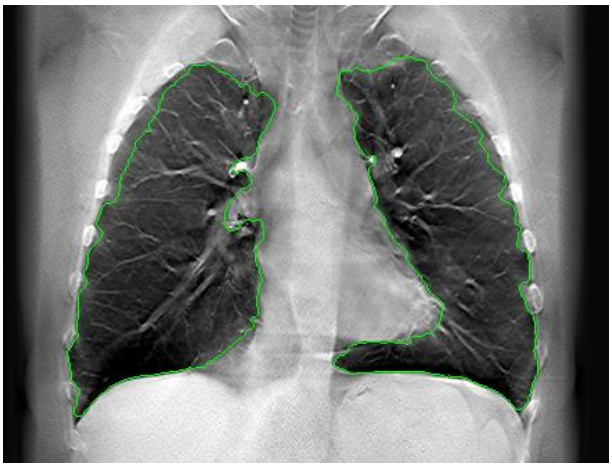

*Fig. 7. Active Contour result after 30 iterations*

To combine the two methods, use active contour model to define the inner side of the lung and use gradient based method, to determine the others. The regions are determined by range of angles and the chosen inner point is used as centerpoint.

The information of adjacent images can be used to fit the segmentation to obtain more reliable masks. The basic method [3] is modified to get a better model. The polar coordinated image is modified, fading the unlikely pixels. Unlike the papers' [3] method, two Gauss functions are used, one for giving a weight to the adjacent images, which depends on how far it is from the calculated image, only the images to the central direction are relevant, other direction's weight is zero. The second Gauss function fits vertically to the image like in the referred article, the center of the function is the adjacent image's path in the current column's selected pixel. Here is the main modification of the function: using an asymmetric Gauss function, with lower width parameter on the farther side from the origin and higher $\sigma$ on the nearer side. This approach is used because the lung area is bigger on central slices, and it shrinks as we are going further from the central slice. $I(x,y)$ is the current pixel, $N$ is a constant for normalization, $G$ is a standard Gauss function, $G_2$ is the asymmetric Gauss function and $O(x,i)$ is the found path's $x$-th point on $i$-th image:

$$I(x,y) = N\sum_i I(x,y)G(i)G_2(O(x,i)-y) \quad (6)$$

In the end the masks may contain acute angles, it is desirable to minimise them, using morphological closing to accomplish this. Different structure sizes on different regions of the lung gives the best result, the biggest structure is used at the inner side of the lungs, and smaller one used on the top of the lungs, the lower area is skipped completely. This approach produces similar result as those of rolling ball, but with less computational complexity [2].

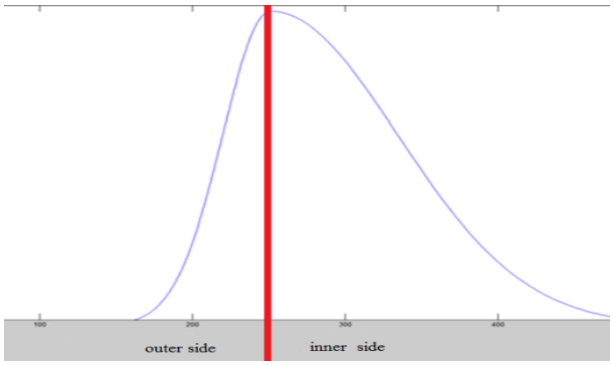


*Fig. 8. Asymmetric Gauss function, with different standard deviation on each side, both sides are normalized to give the same results in the origin.*

## IV. RESULTS OF THE PAPER

Validation of the results is challenging on non-central slices, where blurring could mislead radiologists, so without any further information lung contours created by them can't be considered as reliable segmentation. This problem can be partially solved with simulated tomosynthesis images, which are generated from axial CT slices. The simulated images' characteristics are close to those of the original DTS images. On axial CT images lung masks are generated based on pixel intensity and morphological closing. As a next step these images were projected to coronal slices with similar geometry as the geometry of the DTS. Masks are projected as well, they are used as at least acceptable standard reference, which is useful to calculate metrics too.

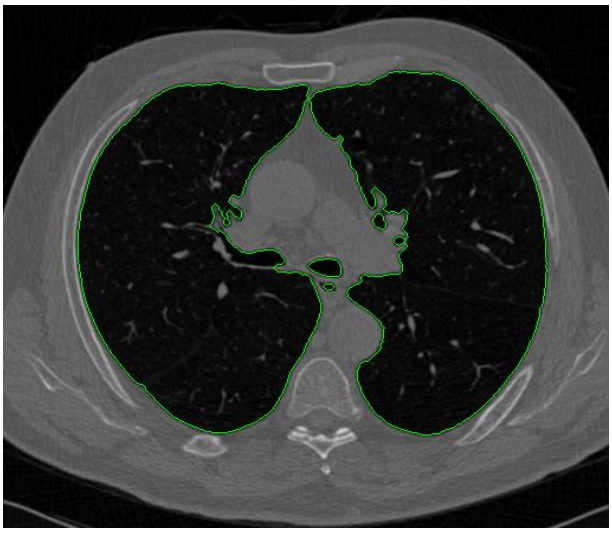

*Fig. 9. Axial CT slice segmented by intensity of the pixel, green line is separating lungs from other parts.*

Three metrics are calculated: overlapping, mean average distance (MAD), which is calculated as average of each discovered points' distance from the nearest reference point. These points' standard deviation is calculated as well.

*Table 1. Results on one image set of 57 central images from 223 images, 130 of them contain lung area according to CT images. Resolution of the images is 512x512 pixels.*

| Result | Overlap | MAD(pixel) | Standard deviation |
|---|---|---|---|
| Both lungs | 0.8508 | 5.175 | 5.943 |
| Left lung | 0.8462 | 5.125 | 6.117 |
| Right lung | 0.8557 | 5.169 | 5.510 |

*Table 1* shows the results on one image set considering only the central images. The numbers shows the robustness of the method as they don't change much from slice to slice. These numbers are close to [3] paper's result, but it isn't clear how their metrics were calculated.

*Table 2. Averaged results using 5 image set's central images. Image resolution is 512x512.*

| Result | Overlap | MAD(pixel) | Standard deviation |
|---|---|---|---|
| Both lungs | 0.7976 | 5.452 | 6.630 |
| Left lung | 0.8089 | 4.507 | 4.770 |
| Right lung | 0.7882 | 6.109 | 7.019 |

The evaluation is done by 5 image set's central images, the results are weighted by the number of central images. An image is considered as a central image if the ribs' cross-sections are sharply visible. Number of central images on the used image set with 223 slice varies from 41 to 57. The aggregated result is shown in *Table 2*.

$$\text{Overlapping is calculated as: } \frac{\sum_{i,j} R(i,j) \cap M(i,j)}{\sum_{i,j} R(i,j) \cup M(i,j)} \qquad (7)$$

where $R(i,j)$ denotes the reference mask's pixel at $i$-th row and $j$-th column and $M(i,j)$ is the segmented mask with same parameters.

Mean Average Distance (MAD) is calculated as:

$$\frac{1}{N}\sum_{i=1}^{N}\sqrt{(R_x(i)-M_x(i))^2+(R_y(i)-M_y(i))^2} \qquad (8)$$

$R$ is the reference and $M$ is the segmented region. $R_x(i)$ refers to the boundary's $i$ point's $x$ coordinate.

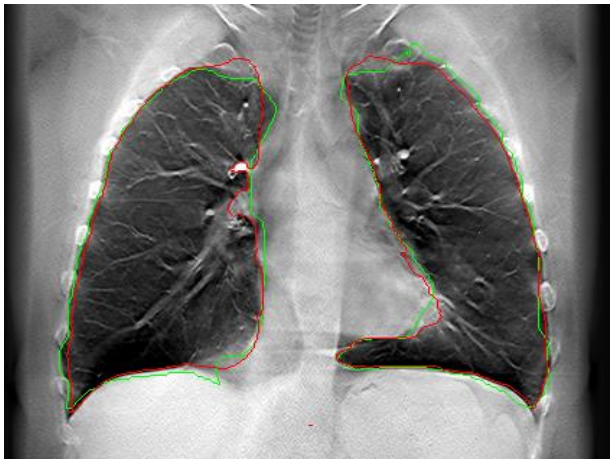

*Fig. 10. On a central image successful segmentation, green line is the method's boundary and red is the reference lung, which comes from a segmented CT-scan.*

*Fig. 11. On a simulated central image partly sucessful segmentation, green line is the method's boundary and red is the reference lung, which comes from a segmented CT.*

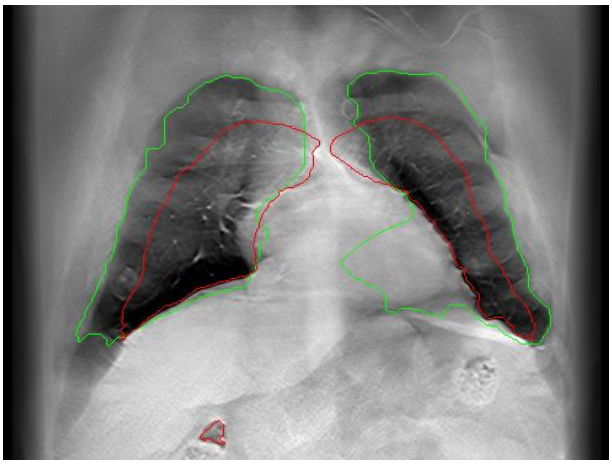

*Fig. 12. On a simulated non-central slice, red line is the reference lung based on CT, it is hard to be separated by radiologists without any help.*

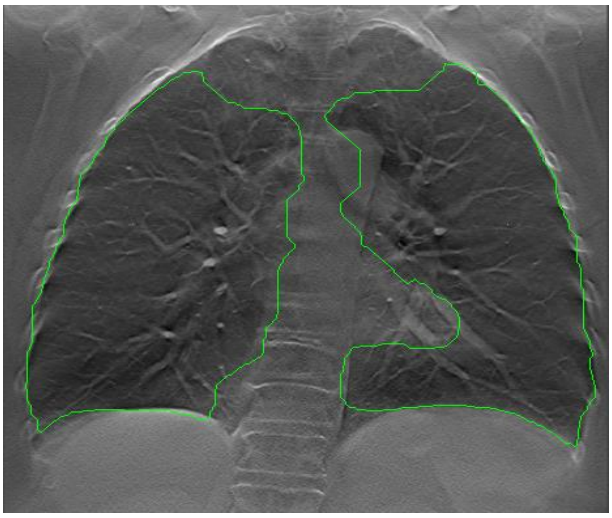

*Fig. 13. On a real DTS image segmentation missed the apex.*

## V. CONCLUSIONS

A combined method can improve the results and may result in more robust solutions. Three different approaches are used to take advantage of each method on different areas of the lungs. Using more complex models is to gain information from adjacent images to improve the incorrectly segmented region on the non-central images.

The inspection focused on the central images, because without them, non-central slices cannot be accurately segmented, and most of the information is concentrated on central images, blurring through adjacent images here can be useful. Further improvement can be reached with creating a model of the lung using statistical methods. There are two ways to do this. The first idea is to create a 2D model for every slice, which describes the coronal shape of the lung. The second solution is building a model, which describes how the lung from the central images is shrinking as going towards the non-central slices. This method can increase accuracy especially on non-central slices. These approaches has many difficulty, one of the biggest problems is that large number of image is required to get a correct model.

## VI. ACKNOWLEDGEMNT

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