# INTACT LUNG EXTRACTION IN THE 2D COMPUTER TOPOGRAPHY IMAGE BY USING A K-COSINE CORNER DETECTION METHOD 

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#### Abstract

Lung cancer, which has a high mortality and the greatest incidence worldwide, can be diagnosed with the aid of chest x-rays or computerized tomography (CT). Some computer-aided diagnosis (CAD) systems have been developed to help physicians diagnose lung cancer. In medical images, however, some nodules attached to the lung boundary are usually segmented as a part of the pleura or mediastinum. This causes these non-isolated nodules to be excluded from the lung parenchyma, which will influence the accuracy of CAD in nodule detection. To solve this problem, this article presents a method known as K-cosine corner detection to find the corner points on a boundary. These corner points are linked under defined criteria. Experimental results shows that a complete and accurate segmentation of lung parenchyma can be carried out, which demonstrates the feasibility of the proposed method.


Key words: K-cosine corner detection, image processing, CT image, non-isolated nodule, curvature.

## 1. INTRODUCTION

Cancer was one of the ten leading causes of death in Taiwan in 2009, accounting for around twenty-eight percent of all deaths (Huang, 2010). Among the many types of cancer, lung cancer is the second most common cancer killer in men but the most common cause of cancer death in women (Huang, 2010). Lung cancer is also a prevalent disease in the United States (American Cancer Society, 2006) and in the UK (Dehmeshki, Chen, Casique \& Karakoy, 2004). The detection of small lung cancers at an early stage is extremely important for the improvement of survival rates and prognosis of the patient. Screening lung cancer by using low-dose computed tomography (CT) has been proposed for many years, as CT images have a higher spatial and temporal resolution than chest radiographs. Many studies have demonstrated that low-dose CT scans can detect peripheral lung cancers at an early stage (Diederich, et al., 2002; Nawa et al., 2002). Hence, CT is a favorable and promising method in the detection of small lung nodules.

To achieve a reliable and high performance computer-aided diagnosis (CAD) system, accurate lung area extraction from CT images must be carried out. These techniques are currently applied to lung segmentation, including gray-level

[^0]thresholding (Armato \& Sensakovic, 2004; Kim, D. Y., Kim, J. H., Noh \& Park, 2003; Korfiatis, Karahaliou, Kalogeropoulou, Lazamtzo \& Costaridou, 2009), active contours (Silveira \& Marques, 2006; Way, et al., 2006), region growing (van Rikxoort, de Hoop, van de Vorst, Prokop \& van Ginneken, 2009), watershed transform (Peter, Boussone, Bergote \& Peyrin, 2008), anatomical model (Brown, et al. 1997), knowledge-based methods (Brown, et al. 2000; Cuevas, Spieth , Carvalho, Abreu \& Koch, 2009), etc. In view of the fact that CT values are lower for the lung area than that for the chest wall, the gray-level thresholding technique can extract substantial parts of lung regions from the CT images.

In fact, the above-mentioned techniques applied to CAD schemes have all demonstrated that they can segment the lung parenchyma from the lung CT images, and CAD systems can detect isolated nodules. However, nodules or vessels in contact with the chest wall may be excluded from the lung parenchyma during the segmentation processes, even though non-isolated nodules do not show as often as the isolated nodules in the CT image inspections. The non-isolated nodules have a high possibility of being cancerous and they should be included in the lung parenchyma after the lung segmentation (Homma, Shimoyama, Ishibashi \& Yoshizawa, 2009). In this study, we calculate the curvature of the contour of the lung parenchyma acquired from the image segmentation. The curvature information may be used to compensate for errors, especially for non-isolated nodules, caused by utilizing a gray-level thresholding technique for segmentation.

## 2. Materials and Methods

### 2.1 CT Image Data

The CT images used in this study consisted of twenty-eight cases, and all patients received the CT screening at Changhua Christian hospital (Taiwan), using a 64-row multidetector CT system (Brilliance CT scanner; Koninklijke Philips Electronics N.V., Amsterdam, Netherlands). The CT scans were performed at the same acquisition parameters for all patients ( $120 \mathrm{kVp} ; 300 \mathrm{mAs}$; detector collimation, 0.625 mm and gantry rotation time, 0.4 second).

The original axial image was a $1-\mathrm{mm}$-thick image, and we selected $5-\mathrm{mm}$ slice thickness for image reconstruction. Each slice had a matrix size of $512 \times 512$, with a pixel size of 0.33 mm . One image was selected per patient to form a 28 -image set, which included eighteen abnormal images and ten normal images. From each patient, a representative slice bearing nodules was chosen according to which nodule had the largest diameter. The abnormal images all had nodules while only a few normal images did not have nodules inside. The diameters of the nodules were between 4 and 28 mm (mean: $13.8 \pm 5.6 \mathrm{~mm}$ ). All image data were collected from January 2007 to September 2008 at Changhua Christian hospital (Taiwan). An experienced radiation oncologist assisted us to contour the malignant nodules on the abnormal images based on the biopsy reports. These image data were all stored in DICOM format, which were transferred digitally from the CT scanner to a desktop computer for image analysis. The desktop computer worked at
2.8 GHz with the Windows ${ }^{\circledR}$ XP operation system. We used MATLAB ${ }^{\circledR}$ as the development environment to write the program and to exhibit the final results of image analysis.

### 2.2 Overall Procedures in Our Scheme

Figure 1 shows the processes of our lung extraction scheme. First, we performed image processing on the original image to obtain the lung parenchyma. Image denoising and enhancement techniques were used to improve image quality and enhance the contrast between different objects. After using the technique of gray-level thresholding segmentation, the lung parenchyma can be roughly extracted from the original CT image. Nevertheless, some undesired parts remained in the segmented image, such as small tracheas or the edge of the CT table. Connected component labeling (CCL) and a background removal algorithm can remove the undesired parts from the image. However, the lung parenchyma acquired from the image processing sometime was not intact, especially when there was a nodule near the pleura. To overcome this drawback, we calculated the curvature of the lung parenchyma (the curvatures of right and left lungs were calculated separately) in the following step. By using the curvature information, juxtapleural objects (i.e., non-isolated pulmonary nodules) could be included in the lung parenchyma for further analysis.


Figure 1. Major procedures in our scheme for lung extraction.

### 2.3 Lung Segmentation

When using the gray-level threshold technique, the lung is segmented from the CT image. However, before applying the gray-level threshold technique, the Wiener filter (Lim, 1990; Sharma \& Van Veen, 1994) and image enhancement methods are utilized to reduce the noise and enhance the contrast of the image, respectively. Contrast enhancement is carried out by the linear stretch method, which is suitable for applying to images with very low or very high variations in brightness. Equation (1) is used for the contrast enhancement of the image,

$$
\begin{equation*}
I_{\text {output }}=\frac{I(i, j)-I_{\min }}{\text { range }} \times 255 \tag{1}
\end{equation*}
$$

where $I(i, j)$ is the intensity of gray level at the location $(i, j)$ in the image, and $I_{\text {min }}$ represents the minimum intensity value in the image. The range in (1) represents the result of subtracting the maximum value and the minimum value in the original gray-level image.

To complete image segmentation, we adopt Otsu's thresholding method (Otsu, 1979) to calculate the best threshold value. The algorithm assumes that the image contains two classes of pixels (background and foreground) and can find an optimal threshold by iterative calculations through all possible values. The aim of Otsu's method is to find the optimum threshold value to separate the two classes where their combined spread (intra-class variance) is minimal. The image is converted to a binary image after the calculation of an optimum threshold by the following criterion:

$$
B(i, j)= \begin{cases}1 & \text { if } f(i, j)>T  \tag{2}\\ 0 & \text { otherwise }\end{cases}
$$

where $T$ is the optimum threshold value obtained from the calculation. $f(i, j)$ is the intensity value at the location $(i, j)$ in the contrast-enhanced image and $B(i, j)$ is the pixel of the binary image. After segmentation, the regions of lung parenchyma should be presented as dark areas in the image and other brighter regions in the contrast-enhanced image are shown as bright areas in the binary image. In order to acquire the lung parenchyma in the image, connected component labeling (CCL) (Fisher, Perkins, Walker \& Wolfart, 2003) and the background removal algorithm (Soille, 1999) are used to process the binary image. The effect of these measures can be explained in a simple way. The bright areas in the binary image are transformed to dark areas and the pixel values of the dark areas surrounding the original bright areas are assigned the value 1 . After these procedures, the lung parenchyma can be roughly acquired. However, the lung regions may still contain some trachea or parts of the chest wall even after the above-mentioned processes. In order to differentiate lungs and other tissues, the CCL technique is used again and the area of each block is calculated. Then, the two blocks with larger areas are selected as the lung regions. By means of the above-mentioned techniques we can obtain the lung parenchyma from the CT image.

### 2.4 Curvature Calculation

Since non-isolated nodules are missed in the lung regions after image segmentation, we utilize a curvature calculation method to obtain the curvature information of the contour of lung. The right and left lungs can be calculated separately with the use of the CCL technique. The contour tracking technique (Lim, 1990) is used to identify the outer margins of the acquired lung parenchyma. The contour information is then used in the curvature calculation. The curvature calculation method we used is the K-cosine corner detection (KCL) algorithm (Sun, et al., 2007), which is defined below. The points at the boundary of the object are defined by $\mathrm{S}=\left\{\mathrm{P}_{\mathrm{i}} \mid \mathrm{i}=1,2,3, \ldots, \mathrm{~m}\right\}$, and the curvature of each boundary point $\mathrm{P}_{\mathrm{i}}$ is defined as:

$$
\begin{gather*}
c_{i}(K)=\cos \theta_{i}=\frac{\vec{a}_{i}(k) \cdot \vec{b}_{i}(K)}{\left\|\vec{a}_{i}(K)\right\|\left\|\vec{b}_{i}(K)\right\|},  \tag{3}\\
-1 \leq c_{i}(K) \leq 1 \tag{4}
\end{gather*}
$$

In Eq. (3), $\vec{a}_{i}(K)=\vec{P}_{i+k}-\vec{P}_{i}, \vec{b}_{i}(K)=\vec{P}_{i}-k-\vec{P}_{i}, \theta$ indicates the angle between $\vec{a}_{i}(K)$ and $\vec{b}_{i}(K)$, the value of $c_{i}(K)$ is between 1 and -1 , and $K \in \mathrm{~N}$ (natural number). The inner product of $\vec{a}_{i}(K)$ and $\vec{b}_{i}(K)$ in (3) provide a geometrical notion of the angle between two vectors. Here, we use the result of Eq. 3 to determine the size of the angle between two nonzero vectors, $\vec{a}_{i}(K)$ and $\vec{b}_{i}(K)$. Therefore, $c_{i}(K)$ denotes the cosine of the angle between $\vec{a}_{i}(K)$ and $\vec{b}_{i}(K)$. K represents the number of pixels between the starting and ending points of a given boundary point. When $c_{i}(K)$ equals -1 , indicating $\theta=180^{\circ}$, the corresponding point is on a flat segment. As $c_{i}(K)$ approaches 1 , the angle $\theta$ approaches 0 , implying the corresponding point is on a sharp angle. When $c_{i}(K)$ approaches $1, \vec{a}_{i}(K)$ and $\vec{b}_{i}(K)$ are in two different segments, the point $P_{i}$ is believed to be a corner point. The corner detection error and curvature threshold are taken into account in the study (Sun, Lo, Yu \& Tien, 2007). Consequently, the value of $K$ is set as 4 in our study, which means we take 4 pixels from the corresponding point to calculate the vectors $\vec{a}_{i}(K)$ and $\vec{b}_{i}(K)$. By using the CCL technique, we can select one side of the lung for curvature calculation. Hence, the curvature information of the right and left lungs is obtained separately.

### 2.5 Criteria for Error Compensation in Lung Segmentation

From the curvature calculation, we can get the coordinate values of possible corner points on the boundaries of the right and left lungs. The corner points are
determined by the value of curvature threshold $T_{c}$. The curvature threshold $T_{c}$ is calculated by using the Eq. (5).

$$
\begin{equation*}
T_{c}=\cos \left(2 \tan ^{-1}\left(\frac{K}{C}\right)\right) \tag{5}
\end{equation*}
$$

where, in this study, the values of $C$ and $K$ are set as 1 and 4 respectively. Hence, the value for the curvature threshold $T_{c}$ is -0.8824 . The curvature values for most boundary points are very close to -1 , which means these points are located on a flat segment of lung contour. If the boundary points with K-cosine values are larger than the specified threshold $T$, these points are defined as the corner points on the boundary. These corner points may be spread on the boundary of the lung. To compensate for errors that occur in lung segmentation, a straight line equation (as seen in Eq. (6) and Eq. (7)) is used to connect any two corner points. In this procedure, the work of connecting any two corner points is done separately for the right and left lungs:

$$
\begin{gather*}
y=m x+b  \tag{6}\\
m=\frac{y_{2}-y_{1}}{x_{2}-x_{1}} \tag{7}
\end{gather*}
$$

where $x_{1}, y_{1}, x_{2}$, and $y_{2}$ represent the coordinate values for two different corner points, and $m$ is the slope of the straight line that connects two points.

Nevertheless, the coordinate values for some of these corner points are very close, and for others are very distant. In order to achieve a better efficiency and performance, the work of line connecting between two points is conducted in the image after lung segmentation under the following criteria. The criteria are: (1) the distance between two points must be less than 40 pixels (the value is set by empirical results); (2) the values of all the pixels on the path that the connected straight line passed through must be 0 . The second criterion is used to avoid the connected straight line passing through regions that are already considered as lung parenchyma after image segmentation. If any two corner points satisfy the criteria, a straight line will be connected between the two corner points. In the segmented binary image, the values of pixels for the lung regions are all 1 . By using these criteria, the work of line connecting can be carried out around the nearby boundary points. The morphologically close operation was then applied to fill the vacant spaces after line-connecting. Following these processes, the non-isolated nodules that are original excluded from the lung areas will be included in the lung parenchyma.

## 3. EXPERIMENTAL RESULTS

### 3.1 Initial Lung Segmentation

The chest CT scan provides transaxial images of the lung of sufficient quality
to detect many lung diseases and abnormalities. In a typical CT image, the right lung shows in the left side of the image and the left lung appears in the right side of the image. Except for lung parenchyma, other tissues or organs of the body also show in the transaxial image of lung, even including the lines produced by the table of the CT machine. Some image processing techniques are needed to obtain adequate segmentation results in order to extract the lung parenchyma from the CT image. The results obtained from the first three procedures (image denoising and enhancement, gray-level thresholding segmentation, and CCL and the background removal algorithm) in our scheme of lung extraction are shown in Figure 2 and Figure 3. After the processes of image denoising and enhancement, the contrast of the CT image is improved and the differences in brightness are favorable for gray-level thresholding segmentation (as seen in Figure 2(b)). By utilizing Otsu's thresholding method, CCL and the background removal algorithm, lung regions can be roughly extracted from the image. The example of the initial image segmentation with the use of Otsu's method is shown in Figure 3(a). After applying CCL and the background removal algorithm, there is still the trachea and some white spots in the binary image (Figure 3(b)). To remove the undesired parts in the image, we compare the sizes of the remaining regions and keep the two largest regions in the image. In general, the correct lung regions can be acquired in this step (as seen in Figure 3(c)).


Figure 2. The initial processes in image processing. (a) An original CT image and (b) the image after the processes of Wiener filter and image enhancement.

### 3.2 Final Lung Extraction after Applying the Proposed Method

After the initial segmentation, we can acquire the major lung areas from a CT image. However, some parts of the lung may be missed in image segmentation as there are non-isolated nodules in the image (as seen in Figure 3(c), there is a non-isolated nodule, indicated by an inserted white arrow, which is excluded from the lung areas). To avoid this situation, contour tracking and K-cosine corner detection is used to achieve intact lung area extraction. The results are shown in Figure 4. The original CT image used to show the results in Figures 2, 3 and 4 is the same. Figure 4(a) shows the contour of the left lung in Figure 2(a), and the corner points defined by the methods of contour tracking and curvature calculation
are marked with small circles. The contour of the left lung shown in Figure 4(a) is plotted according to the image coordinate. Therefore, the staring points for x and y axes in Figure 4(a) are located on the upper left corner in this graph. Straight lines are connected between two corner points under the two conditions (as mentioned in section 2.5). Figure 4(b) exhibits the result of lines connecting two corner points. A close operation of the image is used to fill the gaps produced by the lines and the contour of the lung. The techniques of contour tracking, curvature calculation, line connecting and close operation are used to compensate for these errors caused by previous procedures in image processing. Finally, the non-isolated nodule can be included in the extracted lung areas (as seen in Figure 4(c)). Comparing the lung areas in the original CT image (Figure 2(a)) with the extracted lung areas (Figure 4(c)) by visual observation, both areas are very similar and thus the final result is adequate.


Figure 3. The results of image processing. (a) After gray-level segmentation with the use of an optimum threshold calculated by Otsu's method. (b) A trachea and some white spots remain on the CT image after using CCL and background removal algorithm. (c) The CCL technique is used again and the two blocks with larger areas are preserved. After these procedures, the lung areas can be roughly obtained.

Figure 5 shows the extracted results from three other cases. For case (a), there is a non-isolated nodule in the anterior right lung in the original CT image, and the nodule can be kept in the final segmented image by the use of our methods. In the cases (b) and (c), the nodules are also located in the right lungs. For both cases, the nodules can be included in the final segmented image. These results demonstrate that the techniques we used in this study for lung extraction are effective and practicable. Hence, the proposed method in the study can improve the shortcomings caused by using gray-level thresholding segmentation.

In most cases, the extracted results of lung areas obtained by using our proposed method are consistent with the results from visual observation. Most non-isolated nodules can be included in the final extracted lung areas. However, in some cases there were some drawbacks from using our proposed method. For the images in Figure 6, the upper, middle and lower images, respectively, show the original CT images, the extracted lung areas after image segmentation and background removal, and the final extracted results obtained from our proposed method. The case examples with poor results are shown in Figures 6(a) and 6(b). Except for non-isolated nodules, several bronchi near the boundary of the lung are
included in the final extracted lung areas, as the example shown in Figure 6(a). The case with a large non-isolated nodule (diameter $>28 \mathrm{~mm}$ ) presented in Figure 6(b) is not in the image data mentioned in Section 2.1. This image is used to show a shortcoming in our proposed method. In the upper image of Figure 6(b), there is a non-isolated nodule shown in the posterior right lung. Unfortunately, this non-isolated nodule is not successfully included in the final extracted lung areas. This is a consequence of the non-isolated nodule being too large. In the first criterion for line connecting, we define the distance between two points as being less than 40 pixels. This limitation causes most parts of the non-isolated nodules to be excluded from the final extracted lung areas. Therefore, under the first criterion for line connecting, our proposed method is not suitable for use in cases with large non-isolated nodules. Actually, in our proposed method, the large non-isolated nodule can be included in the final extracted lung area by adjusting the condition of first criterion for line connecting. If the value of the distance between two points is increased in the first criterion for line connecting, the larger non-isolated nodules should be included in the final extracted lung areas. But it may also cause more tissues not belonging to the lungs to be included in the final result the of lung extraction. The CT image shown in Figure 6(c) is from a normal case. This result demonstrates that our proposed method does not cause any adverse effect on the lung extraction result of a normal case. This is because the work of line connecting is only conducted if there are corner points on the contours of the lungs. For this case in Figure 6(c), there are no corner points on the contours of the lungs. The work of line connecting is not performed in this case and the close operation does not influence the final outcome of lung extraction.


Figure 4. Contour information for error compensation in lung segmentation. (a) The contour of the left lung is shown in the figure. (Small circles denote the corner points on the contour). (b) The result of line connecting. (c) The final result of lung extraction.


Figure 5. Extracted results for other three cases obtained by the proposed method. (a) Case 1. (b) Case 2. (c) Case 3.


Figure 6. Three extraction results for lung areas for different cases. The upper, middle and lower images show the original CT images, the extracted lung areas before performing our proposed method, and the final extracted results obtained by using our proposed method, respectively. Two abnormal cases with poor lung extraction are shown in (a) and (b). Case (c) shows the extraction result of a normal case.

## 4. DISCUSSION

In the past, many methods have been proposed to compensate for the errors arising from gray-level thresholding segmentation. Manual editing is an alternative way to obtain satisfactory lung regions after gray-level thresholding segmentation (Denison, Morgan \& Millar, 1986; Kalender, Fichte, Bautz \& Skalej, 1991). A sequence of morphological operations is also an effective technique for smoothing the irregular boundary along the lung region (Hu, Hoffman \& Reinhardt, 2001). Another method, known as a bridging algorithm, can be implemented along each lung segmentation contour to compensate for segmentation error (Goo, et al., 2003). This method calculates the convexity of each point on the contour followed by an imaginary bridge being successively placed tangential to each contour point. Therefore, the indentation is bridged by a new contour segment and some non-isolated nodules could be newly encompassed within the lung segmentation regions. Qiang, Feng and Kunio, (2008) reported that they tracked the contour of the lung region by scanning counter-clockwise all points on the contour one by one. They assigned each current contour point as " A " and then scanned clockwise all contour points to find the other point "B". If points "A" and "B" satisfied three conditions, these two points were connected. This method can also achieve the effect of including a juxtapleural object inside the lung region, but some procedures have to be repeated again and again until all contour points are checked. An active contour model based on a gradient decent-based optimal method was applied in lung extraction (Homma, et al., 2009). The extraction results showed that the non-isolated nodule could be included in the lung region. However, appropriate initial contours must be set prior to solving the local optimum problem.

From the above mentioned methods of compensating for segmentation error, our method is similar to that proposed by Qiang, et al., (2008) and the bridging algorithm (Goo, et al., 2003) in relying on the information from the contour. The K -cosine corner detection method is ordinarily used in fields such as pattern recognition (Bandera, Urdiales, Arrebola \& Sandoval, 1999; Freeman \& Davis, 1977), image matching and boundary presentation, etc. In our study we demonstrate that the K-cosine corner detection method can be applied to biomedical image processing to compensate for segmentation error. According to the curvature information of the lung regions, the non-isolated nodules are included in the segmented lung regions and intact lung area extraction can be accomplished. Generally speaking, our proposed method can provide satisfactory results in lung extraction. Only in some cases a few tracheas and other tissues near the lungs may be extracted and taken as lung area.

## 5. CONCLUSIONS

In this study, we propose utilizing the K-cosine corner detection algorithm in the curvature calculation of the boundary of segmented lung areas. The curvature information is used to compensate for the errors in gray-level thresholding segmentation, which means that non-isolated nodules can be included in the
extracted lung areas. The result of lung extraction in this study is as good as the results obtained by other methods. The advantage of our method is that no initial contour or seed point needs to be set. Our results exhibit good performance in lung extraction and suggest that the proposed technique can be applied in CAD systems.

## REFERENCES

American Cancer Society. (2006). Cancer Prevalence: How Many People Have Cancer? http://www.cancer.org/Cancer/CancerBasics/cancer-prevalence
Armato, S. G. III \& Sensakovic, W. F. (2004). Automated lung segmentation for thoracic CT impact on computer-aided diagnosis. Acad Radiol, 11(9), 1011-1021.
Bandera, A., Urdiales, C., Arrebola, F., \& Sandoval, F. (1999). 2D object recognition based on curvature functions obtained from local histograms of the contour chain code. Pattern Recogn. Lett., 20(1), 49-55.
Brown, M. S., Goldin, J. G., McNitt-Gray, M. F., Greaser, L. E., Sapra, A., Li, K.-T., et al. (2000). Knowledge-based segmentation of thoracic computed tomography images for assessment of split lung function. Medical Physics, 27(3), 592-598.
Brown, M. S., McNitt-Gray, M. F., Mankovich, N. J., Goldin, J. G., Hiller, J., Wilson, L. S., et al. (1997). Method for segmenting chest CT image data using an anatomical model: preliminary results. IEEE Trans Med Imaging, 16(6), 828-839.
Cuevas, L. M., Spieth, P. M., Carvalho, A. R., Abreu, M. G., \& Koch, E. (2009). Automatic Lung Segmentation of Helical-CT Scans in Experimental Induced Lung Injury. Paper presented at the IFMBE Proceedings.
Dehmeshki, J., Chen, J., Casique, M. V., \& Karakoy, M. (2004, 1-5 Sept. 2004). Classification of lung data by sampling and support vector machine. Paper presented at the Engineering in Medicine and Biology Society, 2004. IEMBS '04. 26th Annual International Conference of the IEEE.
Denison, D. M., Morgan, M. D., \& Millar, A. B. (1986). Estimation of regional gas and tissue volumes of the lung in supine man using computed tomography. Thorax, 41(8), 620-628.
Diederich, S., Wormanns, D., Semik, M., Thomas, M., Lenzen, H., Roos, N., et al. (2002). Screening for early lung cancer with low-dose spiral CT: prevalence in 817 asymptomatic smokers. Radiology, 222(3), 773-781.
Fisher, R., Perkins, S., Walker, A., \& Wolfart, E. (2003). Image analysis connected components labeling, from http://homepages.inf.ed.ac.uk/rbf/HIPR2/label.htm
Freeman, H., \& Davis, L. S. (1977). A Corner-Finding Algorithm for Chain-Coded Curves. Computers, IEEE Transactions on, C-26(3), 297-303.
Goo, J. M., Lee, J. W., Lee, H. J., Kim, S., Kim, J. H., \& Im, J.-G. (2003). Automated lung nodule detection at low-dose CT: preliminary experience. Korean J Radiol, 4(4), 211-216.
Homma, N., Shimoyama, S., Ishibashi, T., \& Yoshizawa, M. (2009). Lung area
extraction from X-ray CT images for computer-aided diagnosis of pulmonary nodules by using active contour model. WSEAS Transactions on Information Science and Applications, 6(5), 746-755.
Hu, S., Hoffman, E. A., \& Reinhardt, J. M. (2001). Automatic lung segmentation for accurate quantitation of volumetric X-ray CT images. Medical Imaging, IEEE Transactions on, 20(6), 490-498.
Huang, S. (2010). Cancer remains leading cause of death in Taiwan, Taipei Times. Retrieved from http://www.taipeitimes.com/News/taiwan/archives/2010/06/04/2003474632
Kalender, W. A., Fichte, H., Bautz, W., \& Skalej, M. (1991). Semiautomatic evaluation procedures for quantitative CT of the lung. J Comput Assist Tomogr, 15(2), 248-255.
Kim, D. Y., Kim, J. H., Noh, S. M., \& Park, J. W. (2003). Pulmonary nodule detection using chest CT images. Acta Radiol, 44(3), 252-257.
Korfiatis, P., Karahaliou, A., Kalogeropoulou, C., Lazamtzo, A., \& Costaridou, L. (2009). Texture Based Identification and Characterization of Interstitial Pneumonia Patterns in Lung Multidetector CT. IEEE Trans Inf Technol Biomed, $10,10$.
Lim, J. S. (1990, p. 710). Two-dimensional signal and image processing. Englewood Cliffs, NJ, USA: Prentice Hall.
Nawa, T., Nakagawa, T., Kusano, S., Kawasaki, Y., Sugawara, Y., \& Nakata, H. (2002). Lung cancer screening using low-dose spiral CT: results of baseline and 1-year follow-up studies. Chest, 122(1), 15-20.
Otsu, N. (1979). A Threshold Selection Method from Gray-Level Histograms. Systems, Man and Cybernetics, IEEE Transactions on, 9(1), 62-66.
Peter, Z., Boussone, V., Bergote, C., \& Peyrin, F. (2008). A constrained region growing approach based on watershed for the segmentation of low contrast structures in bone micro-CT images. Patt Recog, 41, 2358-2368.
Qiang, L., Feng, L., \& Kunio, D. (2008). Computerized Detection of Lung Nodules in Thin-Section CT Images by Use of Selective Enhancement Filters and an Automated Rule-Based Classifier. Academic radiology, 15(2), 165-175.
Sharma, R., \& Van Veen, B. D. (1994). Large modular structures for adaptive beam forming and the Gram-Schmidt preprocessor. Signal Processing, IEEE Transactions on, 42(2), 448-451.
Silveira, M., \& Marques, J. (2006). Automatic segmentation of the lungs using multiple active contours and outlier model. Conf Proc IEEE Eng Med Biol Soc, 1, 3122-3125.
Soille, P. (1999). Morphological Image Analysis: Principles and Applications: Springer.
Sun, T.-H., Lo, C.-C., Yu, P.-S., \& Tien, F.-C. (2007, 7-10 Oct. 2007). Boundary-based corner detection using K-cosine. Paper presented at the Systems, Man and Cybernetics, 2007. ISIC. IEEE International Conference on.
van Rikxoort, E. M., de Hoop, B., van de Vorst, S., Prokop, M., \& van Ginneken, B. (2009). Automatic segmentation of pulmonary segments from volumetric chest CT scans. IEEE Trans Med Imaging, 28(4), 621-630.
Way, T. W., Hadjiiski, L. M., Sahiner, B., Chan, H. P., Cascade, P. N., Kazerooni, E.
A., et al. (2006). Computer-aided diagnosis of pulmonary nodules on CT scans: segmentation and classification using 3D active contours. Med Phys, 33(7), 2323-2337.


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