

Evaluation of Lung Size in Patients with Pneumonia and Healthy Individuals^{*}

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(Conference Date: 5-7 March 2020)

(**DOI:** 10.31590/ejosat.araconf39)

ATIF/REFERENCE: Gülay, E. & İçer, S. (2020). Evaluation of Lung Size in Patients with Pneumonia and Healthy Individuals. *Avrupa Bilim ve Teknoloji Dergisi*, (Özel Sayı), 304-309.

Abstract

In recent years, medical image segmentation studies and the need for this issue are increasing rapidly. Semi or fully automatic segmentation of the region to be diagnosed in medical images provides doctors with an important convenience for diagnosis. Especially in some countries where there is a lack of a doctor, it will be provided with a fully automatic segmentation method to assist the treatment without a doctor. In this study, lung x-ray images of patients with pneumonia and healthy individuals were studied. Xray images are advantageous because they are cheaper and easier to interpret than other imaging methods. X-ray images were taken from the ready dataset and the image set consists of chest x-ray images of children under 5 years old. A total of 15 individuals (5 healthy, 5 pneumonia (virus) patients, 5 pneumonia (bacteria) patients) were studied from the data set received. MATLAB program was used for segmentation of lung areas. For segmentation, the images were first reduced to size after being taken to MATLAB. Then, by increasing the contrast of the images, filtering and thresholding process was done with appropriate filter design. Image Segmenter Tool was used for thresholding process. Unlike other studies, active contour method was used to perform lung segmentation. Active contour operation provides energy minimization by drawing skews inside and outside the lung boundaries, iteration continues until equilibrium is achieved, so that the lung boundaries are determined. After active contour procedure, morphological procedures were applied, lung areas were removed and areas were calculated. As a result, semi-automatic segmentation was carried out using the active contour model along with image processing procedures. A significant difference was obtained between the lung sizes of patients and healthy individuals. It is aimed to develop a fully automatic segmentation algorithm that can be generalized for each patient in the future.

Keywords: Chest X-ray (CXR), Pneumonia, MATLAB, Segmentation, Active Contour Model (ACM)

Pnömonili Hastalarda ve Sağlıklı Bireylerde Akciğer Boyutunun Değerlendirilmesi

Öz

Son yıllarda tıbbi görüntü segmentasyonu çalışmaları ve bu konudaki ihtiyaç hızla artmaktadır. Tıbbi görüntülerde teşhis edilecek bölgenin yarı veya tam otomatik segmentasyonu, doktorlara tanı için önemli bir kolaylık sağlamaktadır. Özellikle doktor eksikliğinin olduğu bazı ülkelerde doktor olmadan tedaviye yardımcı olmak tam otomatik segmentasyon yöntemi ile sağlanmış olacaktır. Bu çalışmada pnömonili hastaların ve sağlıklı bireylerin akciğer röntgeni görüntüleri üzerinde çalışılmıştır. Röntgen görüntüleri diğer görüntüleme yöntemlerine göre daha ucuz ve yorumlanması kolay olmasından dolayı avantajlıdır. Röntgen görüntüleri hazır veri kümesinden alınmış olup, görüntü seti 5 yaşın altındaki çocukların göğüs röntgeni görüntülerinden oluşmaktadır. Alınan veri setinden toplam 15 birey (5 sağlıklı, 5 pnömonili (virüslü) hasta, 5 pnömonili (bakterili) hasta) üzerinde çalışma yapılmıştır. Akciğer alanlarının segmentasyonu için MATLAB programı kullanılmıştır. Segmentasyon için, öncelikle görüntüler MATLAB' e alındıktan sonra boyutu küçültülmüştür. Ardından görüntülerin kontrastı artırılarak, uygun filtre tasarımı ile filtreleme ve eşikleme işlemi

^{*} This paper was presented at the *International Conference on Access to Recent Advances in Engineering and Digitalization (ARACONF 2020)*. **Sorumlu Yazar: Erciyes Üniv., Mühendislik Fak., Biyomedikal Böl., Kayseri, Türkiye, <u>ksemra@erciyes.edu.tr</u>

yapılmıştır. Eşikleme işlemi için Image Segmenter Tool kullanılmıştır. Yapılan diğer çalışmlardan farklı olarak akciğer segmentasyonu yapmak için active contour yöntemi kullanılmıştır. Active contur işlemi akciğer sınırları içerisinde ve dışarısında eğeriler çizerek ve enerji minimasyonu sağlar, denge sağlanana kadar iterasyon devam eder böylelikle akciğer sınırları belirlenmiş olur. Active contour işleminden sonra morfolojik işlemler uygulanmıştır, akciğer alanları çıkartılmış ve alanları hesaplanmıştır. Sonuç olarak görüntü işleme prosedürleriyle birlikte aktif kontur modeli kullanılarak yarı otomatik segmentasyon gerçekleştirilmiştir. Hasta ve sağlıklı bireylerin akciğer boyutları arasında anlamlı bir fark elde edilmiştir. Gelecekte her hasta için genellenebilcek tam otomatik segmentasyon algoritmasının geliştirilmesi hedeflenmektedir.

Anahtar Kelimeler: Göğüs Röntgeni, Pnömoni, MATLAB, Segmentasyon, Aktif Kontur Model (AKM)

1. Introduction

Pneumonia is a deadly lung infection caused by bacteria, viruses and parasites. This infection that occurs in the lung occurs in the form of accumulation of inflammatory cells in small lung sacs filled with air called alveoli, and the filling of serum from the blood vessels into this area.

Pneumonia is the leading cause of death among children in developing countries, including India. The World Health Organization estimates that one of three baby deaths at birth is due to pneumonia. Half of these deaths (those with bacterial causes) can be prevented by vaccination [1]. According to the World Health Organization (WHO), pneumonia kills about 2 million children under the age of 5 each year and is consistently estimated to be the only leading cause of childhood deaths. The World Health Organization (WHO) reports that almost all cases (95%) of beginning childhood pneumonia are in developing countries, particularly in Southeast Asia and Africa [2].

Bacterial and viral pathogens are two leading causes of pneumonia. The normal chest x-ray shows open lungs without any abnormal areas of opacification in the image. Bacterial pneumonia typically exhibits focal condensation in the right upper lobe, while viral pneumonia is manifested by a more common "interstitial" pattern in both lungs. Bacterial pneumonia is treated with supportive care for viral pneumonia while seeking immediate referral for emergency antibiotic therapy. Therefore, accurate and timely diagnosis is essential. One of the key elements in the diagnosis is radiographic data because chest x-rays are routinely taken as standard and can help differentiate between different types of pneumonia. However, rapid radiological interpretation of images is not always possible, especially in low resource environments where childhood pneumonia has the highest and highest mortality rates. For this purpose, it is very important in classifying pediatric chest X-rays in detecting pneumonia and also in distinguishing pneumonia to facilitate rapid referrals for children who need urgent intervention [3].

Abhishek Sharma et al., present a new approach to detecting the presence of pneumonia clouds on chest x-rays (CXR). For this, they studied 40 analog breast CXRs from patients infected with normal and pneumonia. Native algorithms have been developed for cutting and removing the lung region from images. Herbaceous threshold value was used to detect pneumonia clouds to separate the healthy part of the lung from pneumonia infected cloudy regions. To obtain a result, it is proposed to calculate the ratio of the area of the healthy lung region to the total lung region. Lung segmentation was done using Python and OpenCV [4].

Mohd Nizam et al., tried to segment the lung using edge-based segmentation. To better detect the edges, they first found the lung edges using the Euler number method and obtained better results. They divided the lung area into sections and calculated their area using a ready-made tool in the MATLAB program and filtering Canny [5].

Preeyanan Pattrapisetwong et al., have tried to develop a Computer Aided Diagnosis (CAD) system for the detection of chest diseases. On chest radiographs, they performed lung segmentation based on shadow filter and local threshold. Their approach consists of three processes: pretreatment, initial lung area estimation, and noise removal. Performance measures (overlap, accuracy, sensitivity, specificity, precision, and F-score) of the proposed method are above 90% [6].

Mesut Togacar et al., utilized lung x-ray images that are accessible for the recognition system developed for the diagnosis of pneumonia. Evolutionary neural network (ENN), one of the deep learning models, was used for feature extraction in the resulting image set. The attributes obtained for the diagnosis of the disease were performed using performance comparisons using different classifiers. As a result of the comparison, a high success rate of 95.8% was obtained with the support vector machines (SVM) used in the classification process. It has been observed in the early diagnosis of deadly diseases such as pneumonia, in the studies that deep learning models give faster and more accurate results [7].

Chest x-ray (CXR) is important for the diagnosis of pneumonia. It is cheaper and easier to interpret than other imaging systems. In this study, it is aimed to remove the lung areas semi-automatically to diagnose pneumonia or any other lung disease by chest x-ray. In line with this goal, active contour method was applied to the lung x-ray images with bacterial and virus pneumonia in Matlab environment. The area of healthy and diseased lung areas has been calculated and the model is intended to operate fully automatically in future studies.

2. Materials and Method

2.1. Materials

The ready-made data set from Kaagle has a total of 5.841 images, 4.265 children with pneumonia (under 5 years of age) and 1.576 chest X-rays from healthy children [8]. After the data was received, MATLAB was used to process the data.

2.2. Method

2.2.1. Active Contour Model

Active contour model (ACM) is the method used to segment the boundaries of an object on the image from other regions in the image. Active contour model is the most widely used model-based method among the degradable models [9]. In degradable models, segmentation is performed with the effect of internal, external and image forces. In order to define the borders of the lungs, closed curves must be located close to the limit to be defined. Curves are then generated as many times as the number of iterations. Internal forces ensure that the curve remains smooth throughout deformation. External forces ensure that the curve is kept at a local minimum. The image forces, on the other hand, ensure that it is directed towards certain points such as the edge in the lung image. Active contour model is a method that enables semi-automatic segmentation by minimizing iteration and energy function [10]. The path to form the curve is determined by minimizing the starting point energy selected by the user so that the lung is close to the border [11]. In other words, it draws a curve on the inside or outside of the lung; With energy minimization created by iterations to take the shape of the curve lung, the curve moves and provides segmentation as in Equation.1 [11,12].

$$E(v) = Eimg(v) + Eint(v) + Eext(v)(1)$$

Here *Eint* indicates the internal force caused by the bend. It is expressed by the tension and flexibility distortions of the contour. *Eimg* image strength; Eext represents external force [13]. At the point where all forces are balanced, the position of the ACM corresponds to the total local minimum. In other words, Equation.2 determines the boundary regions and minimizes the energy directed by external forces and image forces. Equation energy in the Active Contour Model algorithm is as in Equation.2.

Eimg
$$(\vec{v}) = -\int_0^1 P(\vec{v}(s, t)) ds$$
 (2)

As given in Equation.3, P(v(s, t)) is taken equal to the size of the image gradient when pulling the ACM algorithm to the edges [13].

$$P(\vec{v}(s,t)) = |\nabla I(\vec{v}(s,t))|(3)$$

 ∇I (v (s, t)) prevents the algorithm from moving to lower image-energized positions, allowing the image to be softened and the junk spots removed. That is, it directs to more specific details [13]. Equation.4 gives the internal force change.

Eint
$$(\vec{v}) = \frac{1}{2} \int_0^1 a(s) \left| \frac{\partial \vec{v}(s,t)}{\partial s} \right|^2 + \beta(s) \left| \frac{\partial^2 \vec{v}(s,t)}{\partial^2 s} \right|^2 ds$$
 (4)

Here, α (s) and β (s) are functions that regulate the stiffness and tension of the ACM algorithm. Contour tension is controlled by α (s) tension with β (s). Restrictions for voltage are performed by the first terms, making the ACM algorithm act like a dice. It provides the ACM algorithm to act as a thin layer by restricting it with the second order terms for stiffness. In this way, it is aimed to balance the energies [13]. Equation.5 gives external force exchange.

Eext
$$(\vec{v}) = \int_0^1 P(\vec{v}(s)) ds$$
 (5)

This external force equation directs the algorithm to the edge details of the lungs in the lung x-ray image, as given in Equation.6 [13].

$$E(\vec{v}) = -\int_0^1 P\left(\vec{v}(s,t)\right) ds + \frac{1}{2} \int_0^1 a(s) \left|\frac{\partial \vec{v}(s,t)}{\partial s}\right|^2 + \beta(s) \left|\frac{\partial^2 \vec{v}(s,t)}{\partial^2 s}\right|^2 ds (6)$$

This expresses the total energy function of the ACM algorithm as in Equation.7 [13].

$$E(\vec{v}) = -\int |\nabla I(v)|^2 ds + a(s) \int |(v_s)|^2 ds + \beta(s) \int |(v_{ss})|^2 ds$$
(7)

Here, α (s) and β (s) denote the weight parameters, the curve parameter v_s refers to the first derivative according to s and the parameter v_{ss} refers to the second derivative. In line with these equations, progress stops when the curve reaches the lung boundaries with a high image gradient, thereby detecting the lung boundaries [14,15,16].

e-ISSN: 2148-2683

2.2.2. Procedures for Lung Segmentation

Since the size of the chest x-ray images in the data set received is very large, the dimensions of the images were first taken to MATLAB and then it was reduced to [600 600] for easier processing. The reason for doing [600 600] is that it does not give good results in the dimensions below this size. Firstly, the contrast of the adjusted images has been increased and then filtering has been applied to the images.

After filtering, thresholding was done using the Image Segment Tool. The most appropriate threshold value was found by drawing histogram graphics of the images. Active contour was applied after thresholding. Active stroke allows the image to be separated as foreground and background using the active strokes of the image. In this study, the most appropriate active contour iteration value was applied as 100 and "Chan-Vese" mode was used.

Morphological procedures were performed after the active contour procedure. First of all, the gaps were filled, then the lung structure was tried to be improved by performing imdilate and imerode processes. After these procedures, the lungs were removed and their areas were calculated for healthy and sick individuals. Segmentation stages of patients with pneumonia and healthy individuals are given in the figures below.



Figure 1. Respectively: Original x-ray image of the healthy individual, Contrast-enhanced and filtered image, Image with threshold and active contour application, Image with morphological processes, Image with lungs removed



Figure 2. Respectively: Original x-ray image of the patient with pneumonia (virus), Contrast-enhanced and filtered image, Image with threshold and active contour application, Image with morphological processes, Image with lungs removed



Figure 3. Respectively: Original x-ray image of the patient with pneumonia (bacteria), Contrast-enhanced and filtered image, Image with threshold and active contour application, Image with morphological processes, Image with lungs removed



Figure 4. Block diagram of lung segmentation

3. Research Results and Discussion

3.1. Results

As a result of segmentation procedures in MATLAB, total areas of the lungs were found. A total of 15 individuals were studied, including 5 healthy individuals, 5 patients with pneumonia (virus) and 5 patients with pneumonia (bacteria). A clear difference was observed between lung sizes between healthy individuals and patients with pneumonia. As shown in Table 1, the average lung area of healthy individuals is 115575.2, the average lung area of patients with pneumonia (virus) is 69005.4, while the average lung area of patients with pneumonia (bacteria) is 60656.4.

Participant	Healthy	Patient	Patient
Groups	Group	Group with	Group with
		Pneumonia (virus)	Pneumonia (bacteria)
Participiants			
	94080	35141	27883
1.Individual			
	129501	63478	69352
2.Individual			
	123272	75901	79633
3.Individual			
	106665	86009	69527
4. Individual			
	124358	84748	56887
5. Individual			
	115575,2	69005,4	60656,4
Average Lung Areas			

Table 1: Lung Areas and Average Lung Areas

3.2. Discussion

There are many studies reporting good segmentation results for CXR images. For example, Sharma et al., segmented the lungs with the Herbaceous method by destroying pneumonia clouds in the segmentation process. Since pneumonia clouds are not seen in the lung image after herbaceous thresholding, this ratio is expected to be much lower than it is calculated for healthy lungs without cloud. It is aimed to calculate the ratio of the lung area to the area of the total lung area after herbaceous thresholding [4].

In the study by Saad et al., the segmentation process starts by detecting the lung edge using canny edge detection filters. Euler number method is applied to improve edge detection. The morphology method is then used to improve the lung edge so that the final output of the lung region can be produced. After performing the segmentation task, it is compared with the GT image to check the output similarities in the form of the lung region mask. Jaccard Similarity Coefficient was used to calculate the similarity in the evaluation. The value obtained from the test is moderately high, although it does not exceed the score of previous researchers [5].

There have been many studies on the deep learning model in the biomedical field recently. It was understood in the analysis results of the studies that the deep learning gave effective results. The convolutional neural network (CNN) model has been observed to be effective in the biomedical field as well as in other fields, in a study by Toğaçar et al., here, the most important feature of the CNN model is faster, more efficient and most importantly, automatically generating attributes and reflecting this on the result. Application of this model on chest x-ray images; It is important for early diagnosis of pneumonia. A feature extraction set was obtained using the AlexNet architecture. Classification was performed between image sets using the properties obtained, decision tree (DT), linear discrimination analysis (DAA), linear regression (LR), support vector machines (SVM), nearest neighbor (NN) and softmax classifiers. The effect of using the principal component analysis (PCA) on the results was analyzed and it was seen that it saves time. The most successful classifier among the classifiers used was the SVM classifier with a success rate of 95.8% [7].

4. Conclusion

In this study, pulmonary segmentation was performed by applying active contour method to x-ray images of the lung. There was a significant difference in the lung sizes of patients with pneumonia and healthy individuals. However, segmentation was performed semi-automatically and with additional procedures for patient images due to the lung areas behind the bone tissues and the contrast in the image. In the future, it is aimed to develop an automated segmentation algorithm to identify lung areas that can be generalized for each patient.

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