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Lung Field Segmentation in Chest Radiographs from Boundary Maps by a Structured Edge Detector

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ABSTRACT

Lung field segmentation in chest radiographs (CXRs) is an essential preprocessing step in automatically analyzing such images. We present a method for lung field segmentation that is built on a high-quality boundary map detected by an efficient modern boundary detector, namely, a structured edge detector (SED). A SED is trained beforehand to detect lung boundaries in CXRs with manually outlined lung fields. Then, an ultrametric contour map (UCM) is transformed from the masked and marked boundary map. Finally, the contours with the highest confidence level in the UCM are extracted as lung contours. Our method is evaluated using the public JSRT database of scanned films. The average Jaccard index of our method is 95.2%, which is comparable with those of other state-of-the-art methods (95.4%). The computation time of our method is less than 0.1 s for a 256 × 256 CXR when executed on an ordinary laptop. Our method is also validated on CXRs acquired with different digital radiography units. The results demonstrate the generalization of the trained SED model and the usefulness of our method.

***Index Terms*—**chest radiography, lung field segmentation, boundary detection, structured edge detector

INTRODUCTION

Chest radiography (chest X-ray) is a diagnostic imaging technique widely used for lung diseases. The automatic segmentation of lung fields has received considerable attention from researchers as an essential preprocessing step in automatically analyzing chest radiographs (CXRs) [1-7]. An accurate automatic segmentation of lung fields can save physicians' efforts for manual identification of the lung anatomy. In addition, this process is a necessary component of a computer-aided diagnosis system for detecting lung nodules [8]. The segmentation of lung fields is also useful for the anatomic region-based processing of CXRs, such as contrast enhancement of lung regions and bone suppression [10].

DIGITAL IMAGE PROCESSING

Theory of Digital Image Processing

An image is represented technically as two dimensional function f(x, y) which represents the intensity of selected pixel and here f denotes the intensity and x,y terms is termed as sparsity of pixel or weight of the pixel which gives the exact location of pixel in an digital image. Literally the digital image is also termed as "an image is not an image without any object in it".

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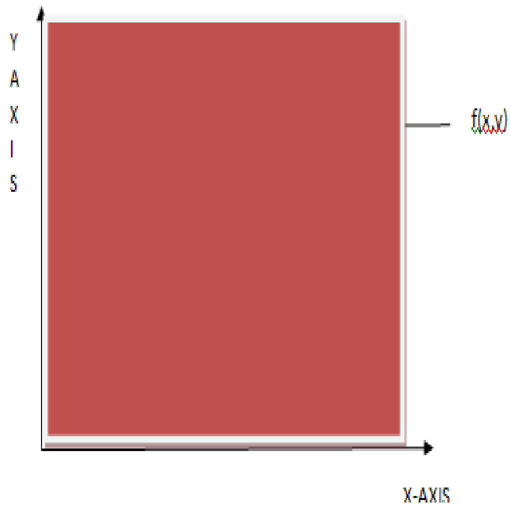
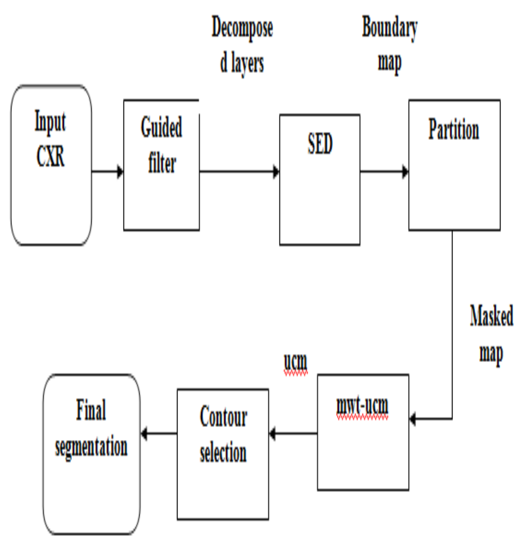


LITERATURE SURVEY

S. Candemir, S. Jaeger, K. Palaniappan, J. P. Musco, R. K. Singh, X. Zhiyun, A. Karargyris, S. Antani, G. Thoma, and C. J. McDonald,

The National Library of Medicine (NLM) is developing a digital chest X-ray (CXR) screening system for deployment in resource constrained communities and developing countries worldwide with a focus on early detection of tuberculosis. A critical component in the computer-aided diagnosis of digital CXRs is the automatic detection of the lung regions. In this paper, we present a nonrigid registration-driven robust lung segmentation method using image retrieval-based patient specific adaptive lung models that detects lung boundaries, surpassing state-of-the-art performance. The method consists of three main stages: 1) a content-based image retrieval approach for identifying training images (with masks) most similar to the patient CXR using a partial Radon transform and Bhattacharyya shape similarity measure, 2) creating the initial patient-specific anatomical model of lung shape using SIFT-flow for deformable registration of training masks to the patient CXR, and 3) extracting refined lung boundaries using a graph cuts optimization approach with a customized energy function. Our average accuracy of 95.4% on the public JSRT database is the highest among published results. A similar degree of accuracy of 94.1% and 91.7% on two new CXR datasets from Montgomery County, MD, USA, and India, respectively, demonstrates the robustness of our lung segmentation approach.

Proposed Method



A. Overview

This work aims to develop a practical and useful method for automatically segmenting lung fields in CXRs. The core of our proposed method is the effective use of the lung boundary map produced by SED. As shown in Fig. 2, an input CXR was first normalized into the intensity range [0, 1] and decomposed as the input of SED to the base and detail layers by a guided filter [22]. Next, a boundary map was produced by the

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SED model trained for detecting the boundaries of lung fields. From the boundary map and the input CXR, the ribcage and spinal centerline were extracted. These segments were used to partition the CXR into the right and left thorax areas as well as clean the boundary map for further processing. Subsequently, the candidate lung regions and contours were generated by using MWT and UCM transforms (mwt-ucm). Finally, the contours with the highest confidence level were selected as the right and left lung contours. To effectively perform segmentation, each step of the proposed method employed highly efficient algorithms for executing the corresponding functions, including guided filter [22], dynamic programming, and watershed transform (WT).

EXPERIMENTAL RESULTS

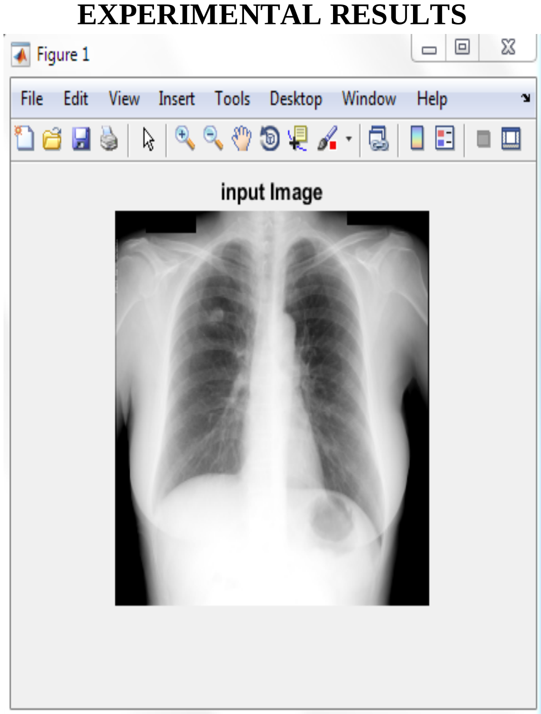

fig1: input image

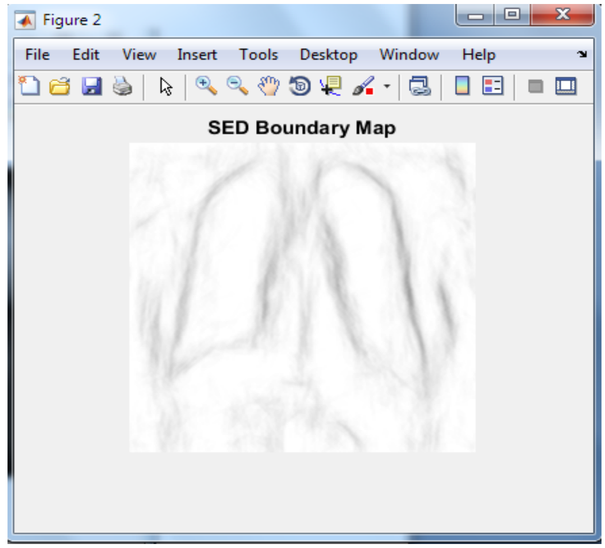

fig2: sed boundary map of input image

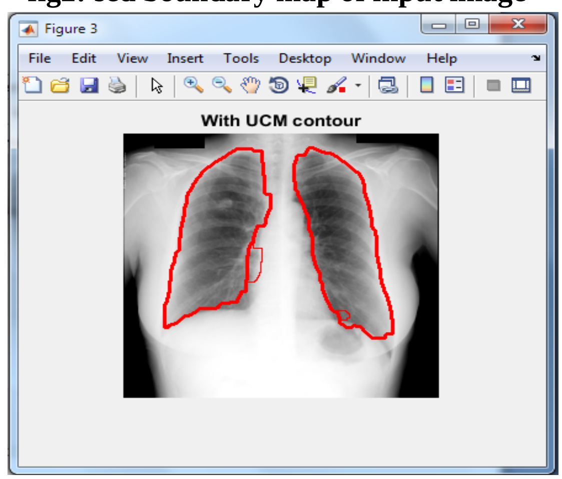

fig3: ucm contour

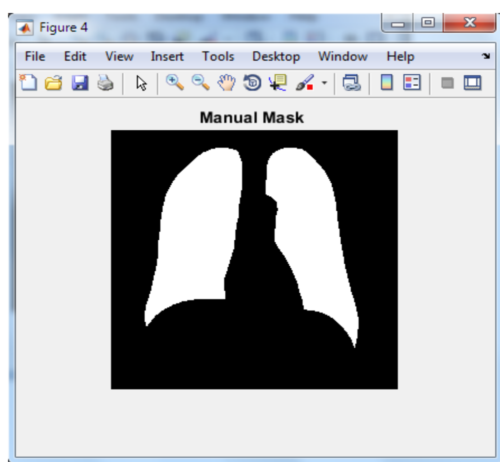

fig4: manual mask of the image

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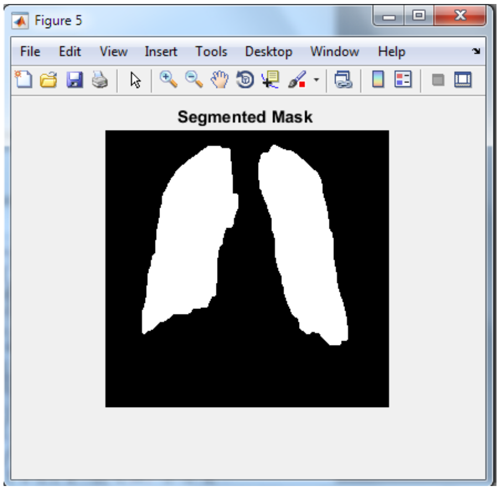

fig5: final segmentation output image

DISCUSSION AND CONCLUSION

Our method for lung field segmentation employed structured random forests to detect lung boundaries. In principle, modern boundary detectors, such as DeepEdge [17], Oriented Edge Forests [29], and HED [18], can be trained to detect these particular boundaries of lung fields. Among modern boundary detectors, SED exhibits high efficiency, which promotes a fast and practical procedure of lung field segmentation.

The segmentation performance of our method can be further improved. One technique is to combine pixel classification results and the boundary map detected by SED. Another approach is to combine shape models with the boundary map. However, computation time and algorithm complexity increase when these methods are used. A direct approach is to reduce the false boundary responses of SED. In general, a large number of training samples can lead to a relatively good performance of prediction models. We can collect many CXRs with the manual segmentation ground truth to train a SED. Variations in lung field boundaries can be effectively identified using the trained SED.

The segmentation of abnormal lungs is typically difficult. We should develop appropriate rules to address abnormal cases and improve the robustness of SEDUCM. As shown in Fig. 11, our SEDUCM method produces some unreasonable lung contours. The resulting notches by the discontinuity of the detected lung contours can be linked by the smooth curves. Alternatively, the active contour model [30] with a few iterations can be applied to refine the lung contours but with a long computation time.

In summary, we present an effective and efficient lung field segmentation method that can achieve state-of-the-art segmentation accuracy and fulfill the practical requirement of real time. Our method uses a SED to detect lung boundaries. The results demonstrate that effective detection of lung contours using SED and mwt-ucm transform is feasible. Our method can be adopted to simplify approaches for analyzing CXRs.

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