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A Robust Technique for Lung Field Segmentation in Chest Radiographs by Using the Structured Edge Detector

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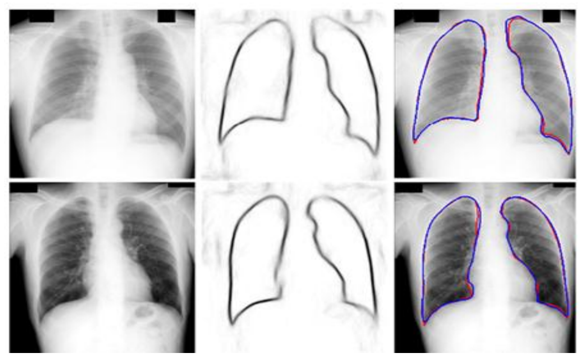
***Abstract*- Lung field segmentation in chest radiographs (CXRs) is an essential preprocessing step in automatically analyzing such images. We present a method for lung field segmentation that is built on a high-quality boundary map detected by an efficient modern boundary detector, namely, a structured 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- Brain region segmentation, skull stripping, MRI, convolutional neural network.

I. 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. 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. However, an accurate segmentation of lung fields in CXRs remains a challenge for several reasons. Lung fields exhibit large anatomical shape variations, including varying heart dimensions or other pathologies, across different patients in 2D radiographs. Lung fields in CXRs also contain several superimposed structures, such as lung vasculatures, clavicles, and ribs, which do not form the borders of lung fields.



The strong edges at the rib and clavicle regions may result in inaccurate location of landmarks or inaccurate lung contours in some lung field-segmentation approaches. In addition, segmenting the lung apex is difficult because of the varying intensities in the upper clavicle bone region. A recent study has introduced an atlas-based method that exhibits state-of-the-art performance; in this method, the CXR database of pre-segmented lung fields is used as the anatomical atlas, and the SIFT Flow algorithm is employed to align the CXR with the atlas [1]. In general, atlas-based methods are very time consuming. Lung segmentation can be refined through post-processing typically by using graph cuts [1, 12]. Among the energy functions for graph cuts, the boundary term is critical to improve segmentation accuracy. An accurate detection of lung boundaries is crucial to realize an accurate and simple automatic segmentation of lung fields. Active shape models (ASM) and active appearance models (AAM) can incorporate low-level appearance cues and high-level shape priors, and have been successfully applied to lung field segmentation [4, 6]. In general, shape model-based methods tend to produce average shapes and are ineffective with abnormal cases. The segmentation performance of shape models relies on the approximation accuracy of the initial model. Hybrid methods produce improved results by fusing several techniques, but the segmentation algorithm is sophisticated and time consuming [4]. A recent study has introduced an atlas-based method that exhibits state-of-the-art performance; in this method, the CXR database of pre-segmented lung fields is used as the anatomical atlas, and the SIFT Flow algorithm is employed to align the CXR with the atlas [1]. In general, atlas-based methods are very time consuming. However, lung boundaries are not always located on well-defined edges, where the gradient magnitude is maximum along the gradient direction. Simple gradients or derivatives of CXRs are insufficient for handling many anatomical structures and textures. Hence, an accurate detection of lung boundaries in CXRs is traditionally considered to be highly difficult.

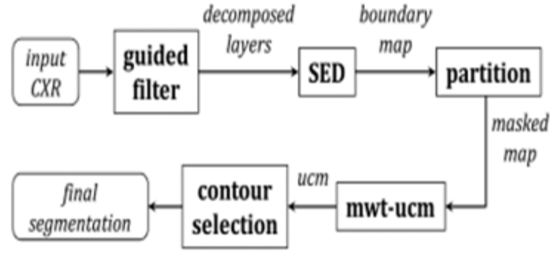
II. LITERATURE SURVEY

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 The delineation of important structures in chest radiographs is an essential preprocessing step in order to automatically analyze these images, e.g., for tuberculosis screening support or in computer assisted diagnosis. We present algorithms for the automatic segmentation of lung fields in chest radiographs. We compare several segmentation techniques: a matching approach; pixel classifiers based on several combinations of features; a new rule-based scheme that detects lung contours using a general framework for the detection of oriented edges and ridges in images; and a hybrid scheme. Each approach is discussed and the performance of nine systems is compared with inter observer variability and results available from the literature. The best performance is obtained by the hybrid scheme that combines the rule-based segmentation algorithm with a pixel classification approach. We have developed a knowledge-based approach to lung boundary interpretation in chest X-rays. Within modular system architecture, an explicit anatomical model is matched to image data by mapping both to a common feature space for comparison. The knowledge-based approach augments low-level segmentation techniques by allowing high-level image interpretation. In our approach, domain knowledge provides guidance for object recognition. Using the hierarchy implied by relationships in the model, the internecine and control system automatically schedules the identification of anatomical structures.

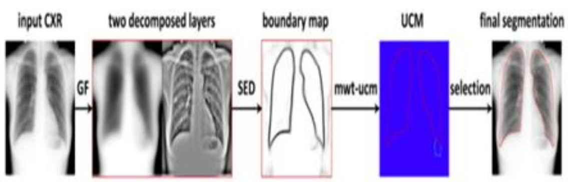
III. PROPOSED METHODOLOGY

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].

Flowchart of our proposed method for lung field segmentation



Next, a boundary map was produced by the 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). We first reviewed the SED proposed by Dollár and Zitnic [16]. Dollár and Zitnic formulated the edge detection task in a general structured learning framework where a random decision forest [23, 24] is exploited to general structured output spaces.



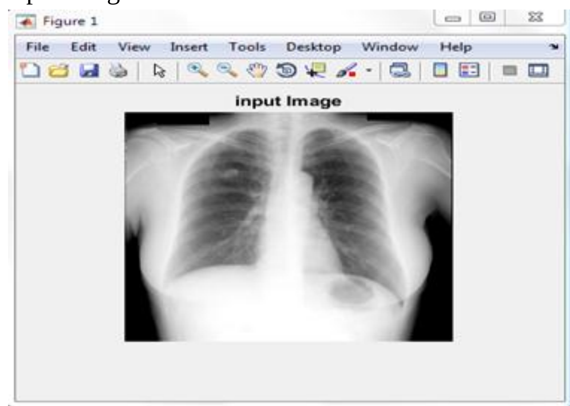
Given a node j and a training set S⊂X×Y, the training goal of the decision tree is to find parameter θj that maximizes the information gain criterion Ij defined by

$$I_j = I(S_j, S_{jL}, S_{jR}), \qquad (1)$$

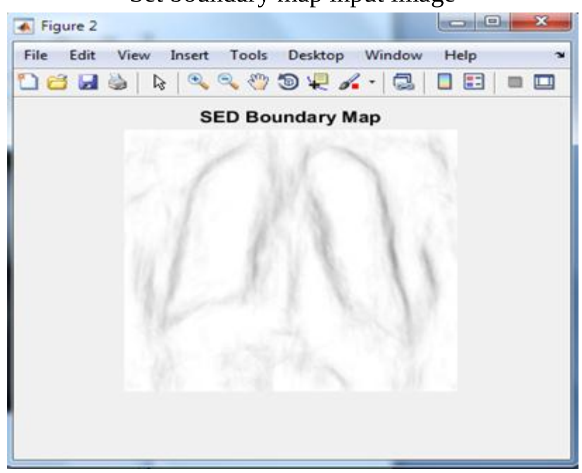
At each internal node of the tree, a feature is chosen to split the incoming training samples to maximize some criteria. A random decision forest comprises multiple independent decision trees [23, 24]. Given a sample, the predictions from the set of decision trees are combined into a single output by using an ensemble model. We adopted the contour-based hierarchical segmentation method proposed by Arbelaez et al. [19, 20] to generate candidate segments of lung field from the MWT or WT of the masked boundary map. The result of this hierarchical segmentation method is a weighted contour image called UCM, the values of which reflect contour strength and the contrast between neighboring regions [19]. This method generally preserves the global contours of objects while providing hierarchical segments. Such segments are obtained using a greedy graph-based region merging algorithm. Let G (P0, K0, W (K0)) denote an initial graph, where the nodes are the regions P0 generated.

IV.EXPERIMENTAL RESULTS

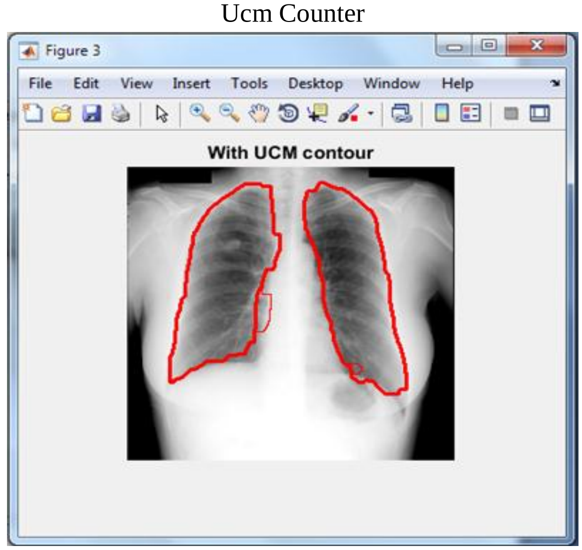
Input image.



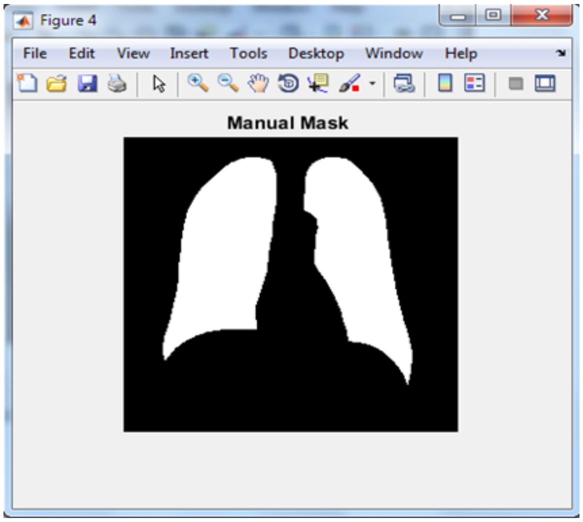
Set boundary map input image



Ucm Counter



Final Segmentation Output Image



V.EXTENSION METHOD

Active contour is a type of segmentation technique which can be defined as use of energy forces and constraints for segregation of the pixels of interest from the image for further processing and analysis. Active contour described as active model for the process of segmentation. Contours are boundaries designed for the area of interest required in an image. Contour is a collection of points that undergoes interpolation process. The interpolation process can be linear, splines and polynomial which describes the curve in the image. Different models of active contours are applied for the segmentation technique in image processing. The main application of active contours in image processing is to define smooth shape in the image and forms closed contour for the region. Active contour models involve snake model, gradient vector flow snake model, balloon model and geometric or geodesic contours.

Active contours can be defined as the process to obtain deformable models or structures with constraints and forces in an image for segmentation. Contour models describe the object boundaries or any other features of the image to form a parametric curve or contour. Curvature of the models is determined with various contour algorithms using external and internal forces applied. Energy functional is always associated with the curve defined in the image. External energy is defined as the combination of forces due to the image which is specifically used to control the positioning of the contour onto the image and internal energy, to control the deformable changes. Constraints for a particular image in the contour segmentation depend on the requirements. The desired contour is obtained by defining the minimum of the energy functional. Deforming of the contour is described by a collection of points that finds a contour. This contour fits the required image contour defined by minimizing the energy functional.

VI.CONCLUSION

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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