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Low order adaptive region growing for lung segmentation on plain chest radiographs

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A B S T R A C T

This study proposes a computer-aided region segmentation for the plain chest radiographs. It incorporates an avant-garde contrast enhancement that increases the opacity of the lung regions. The region of interest (ROI) is localized preliminarily by implementing a brisk block-based binarization and morphological operations. Further improvement for region boundaries is performed using a statistical-based region growing with an adaptive graph-cut technique that increases accuracy within any dubious gradient. Assessed on a representative dataset, the proposed method achieves an average segmentation accuracy of 96.3% with low complexity on 256p resolutions.

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1. Introduction

Plain chest X-Ray (CXR) has extensively been utilized as a salient modality for diagnosing any pulmonary disorder in humans [1]. Based on the standard for protection against the radiation exposure on humans [2], the CXR screening is performed at an effective dosage; thus inducing a low level of radiation risk. An ENT (ear, neck, and throat) radiologist is trained to intuitively recognize any pulmonary disorder based on the particular discrepancies (e.g. nodule, mass tissue, or deformation) that occur within the lung regions [3,4]. This subjective approach relies entirely on the condition and the experience of the examiner.

As the level of air pollution increases, the contingency of a person to suffer from a pulmonary disease shall increase. More patients will be advised by their physician to perform CXR screening, which adds more workloads to the ENT radiologist. Therefore, these circumstances will increase the possibility of false diagnosis simply due to fatigue. Staiger et al. [5] predict that this condition will potentially worsen due to the workforce shortage in most countries. Motivated by the aforementioned reasons, various computer-aided diagnosis (CAD) systems with a predefined scope of respiratory disease have been developed to extract any essential information such as the lung regions.

Prior studies [1,6,7] agreed that CAD-based systems increase the diagnosis quality by signifying the distinctive characteristics of any particular respiratory disease. The CAD systems also offer a remote solution for any area, where the presence of radiologists is minor. A robust CAD system able to endure various anatomical challenges, which are depicted in Fig. 1, such as 1) wide variance of pixels within the lung apices, hila, and the great vessels of heart; 2) attenuated lung boundaries caused by gaseous trachea and fundus in the upper respiratory tract and hemi-diaphragm, respectively; 3) local maxima patterns generated by rib-cages and clavicles; 4) convoluted structures over the costophrenic angles and vacillating shape of the lungs; and 5) any physical discrepancy.

In the past few years, different studies have been conducted to develop CAD-based systems that are capable of segmenting the lung regions over the human torso on CXR images. The rule-based reasoning and the pixel classification-based techniques are two main folds of lung segmentation techniques, of which details and drawbacks are introduced in Section 2. Nevertheless, with recent development in GPU-based systems, more implementations of deep neural network techniques have been applied to develop the lung segmentation algorithm [8,9]. Although the trade-off between the complexity and the segmentation accuracy on deployment can be minimized, the methods massively exploit the graphical mem-

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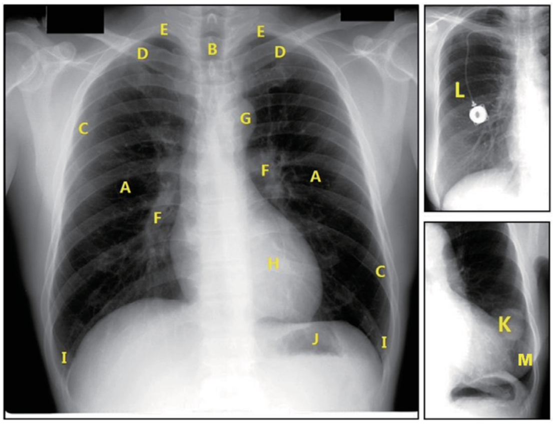

Fig. 1. The distinctiveness of CXR comprises numerous sections of chest relics: lungs (A), trachea (B), rib cages (C), clavicles (D), lung apices (E), hilum (F), aortic arch (G), heart (H), costophrenic angles (I), fundus (J), nodule (K), alienated unit (L) and breast tissue (M).

ory and computing power of GPU-based system which limits the applicability to certain hardware specifications.

In this study, an efficient method for segmenting lung regions from the CXRs is proposed. The proposed method comprises of four stages: Initially, a contrast enhancement specifically increases the gradients between the lungs and their surrounding regions (both bony structures and other soft tissues). The foreground, which incorporates the upper torso region, is extracted using an intelligent block-based binarization [10,11]. Then, lung regions are excluded from the foreground through a series of spatial-based processing: the first derivative of Gaussian, morphological analysis, and the statistical-based region growing. As the final stage, an adaptive graph cut technique is implemented to locally refine the preliminary lung boundaries.

The remainder of this research paper is organized as follows. Section 2 presents few studies, which are related to this work. The proposed method is elaborated in details in Section 3. Comprehensive assessment of the proposed method through objective and subjective measures are presented in Section 4 with the discussion in Section 5. Finally, the conclusion is stated in Section 6.

2. Related works

2.1. Related studies in lung segmentation

Numerous CAD-based systems for localizing lung regions have been developed over the past few decades. A comprehensive study [12] maps the advancements of lung segmentation technique into three main streams. The rule-based reasoning is a parametric learning algorithm that utilizes a set of rules to transform the image into desirable data through a series of processing: the pixel binarization [13], the edge detection [14,15], the morphological operations [13], the geometrical fitting models [15], and the region growing [14]. These schemes provide adequate accuracy if the features are well extracted.

Pixel classification-based method utilizes general classifiers, such as the neural network and the Markov random field modeling, to extract the lung regions. This supervised learning scheme classifies the pixel values into two classes, which are the lung regions and their surrounding areas using a set of lung masks [15,16]. In addition, Suzuki et al. [17] proposed massive training artificial neural network that utilizes a non-linear filter to suppress the rib cages.

Active shape model (ASM) [18] resembles contour(s) using deformable statistical model(s) that comprise a set of landmark points. This scheme had been extensively used in the prior lung segmentation methods [16,19] and achieved fair accuracy with a minor drawback in overcoming local extrema, e.g. clavicles and ribcages. Further optimization of the cost functions has been proposed in [20–22]. Aside from the ASM, the active appearance models (AMM) and multi-scale pixel classification [16] adapt the multi-scale filter bank of Gaussian derivatives and the k-nearest neighbor classifier.

Another approach that combines the prior schemes is the hybrid method; for instance, Coppini et al. [23] utilized a closed fuzzy-curve algorithm, of which membership functions are determined by the Kohonen networks to model the lung boundaries. Candemir et al. [24] proposed a lung segmentation method that mainly analyzes input using the content-based image retrieval method for determining a feature for the SIFT-flow registration with the final graph cut.

2.2. System overview and contributions

This study proposes a fully automated computer-aided detection for lung segmentation on plain chest radiograph (CXR) images. The overall diagram of the proposed method is illustrated in Fig. 2, which consists of four main modules. In the preliminary stage, a novel contrast enhancement technique is proposed using the bisected upper-lower histogram analysis to enhance the image contrast by significantly increasing the intensities of soft tissues and bone structures and increasing the opacities of the lung regions. The foreground of CXR (i.e. torso region) is then extracted with the improved intelligent block-based binarization that is designed to efficiently localize the torso region, which effectively covers the lung regions; while the soft tissue regions are localized with the isodata binarization. A preliminary lung mask is then generated by mathematically incorporating the torso mask and the binarized CXR through the independently-designed spatial image analysis. To reduce the false positive and false negative pixels in the preliminary lung mask, the region growing technique is implemented based on the 8-neighboring blocks to evaluate each pixel within the boundary of the localized regions. Using the state of the art of graph cut technique, the proposed method adaptively improves the boundaries in the grown lung mask to reduce the uncertainty especially pixels with fine details.

3. Proposed method

The proposed method comprises of four straightforward stages that are depicted in Fig. 2 including image preprocessing, foreground detection, statistical region-based segmentation, and graph cut-based refinement. In the statistical region-based segmentation, morphological operations, i.e. dilation and erosion, are implemented to spatially analyze any bitmap as:

$$in \oplus SE = \max_{(x',y') \in SE(x',y') \neq 0} in(x+x', y+y'), \quad (1)$$

and

$$in \ominus SE = \min_{(x',y') \in SE(x',y') \neq 0} in(x+x', y+y'), \quad (2)$$

where *in* and *SE* denote the input bitmap and the structuring element for the morphological operation, respectively.

3.1. Image preprocessing

In general, the CXRs are acquired using the high kV method, which may result in low contrast profile as illustrated in Fig. 3a. Prior to the proposed segmentation, the image contrast of the acquired input CXR (I) is improved through the proposed contrast

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