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Segmenting Anatomy in Chest X-rays for Tuberculosis Screening

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Abstract— **In this paper we describe the development of a screening system for pulmonary pathologies (i.e. pneumonia, tuberculosis) application in global healthcare settings. As a first step toward this goal, the paper presents a novel approach for detecting lungs and ribs in chest radiographs. The approach is a unified method combining two detection schemes resulting in reduced cost. The novelty of our approach lies on the fact that instead of using pixel-wise techniques exclusively we used region-based features computed as wavelet features that take into consideration the orientation of anatomic structures. Initial results are described. Next steps include classification of non-rib lung regions for radiographic patterns suggesting tuberculosis infection.**

I. Introduction

Researchers at the National Library of Medicine (NLM) in collaboration with Indiana University School of Medicine, AMPATH (Academic Model Providing Access to Healthcare, http://www.iukenya.org) which is the largest AIDS treatment program in the third world, and Moi University in Eldoret, Kenya, are working to develop a mobile digital chest x-ray imaging and screening system for detecting tuberculosis (TB) and other lung diseases in remote or rural areas in Kenya, and possibly as a model for other countries.

TB is one of the most common causes of mortality [1]. An estimated 9 million new cases appear annually and about one-third of the world's population is infected with *Mycobacterium tuberculosis*, a bacterium that causes most cases of TB. Despite considerable progress in diagnosis and treatment to eradicate the disease, TB remains a major health threat. The problem has been exacerbated by opportunistic infections of HIV positive populations and the emergence of multi-drug resistance strains.

Tuberculosis is most prevalent in sub-Saharan Africa and Asia, where widespread poverty and malnutrition reduces the patients' resistance to the disease. Our goal is to develop image-processing based systems that can identify the features that can best describe and screen for the subtle manifestations of TB in chest x-rays (CXRs). The approach is consistent with current medical practice of medical expert review of PA chest x-rays to confirm existence of disease after a positive skin test.

The project consists of two parallel phases: a) hardware utilization and b) software development. Regarding hardware: the goal is to achieve quick and inexpensive deployment of portable chest x-ray machines in rural areas. These machines can be mounted on off-terrain vehicles and are capable of producing CXRs rapidly to screen affected populations. The software development phase includes development of algorithms for screening digital CXRs for TB and other pulmonary pathologies. As a first step in this process, it is necessary to identify relevant anatomical regions of interest, viz. lungs, and within these the ribs. The latter is for exclusion from further analysis with an aim towards minimizing noise and improving screening accuracy.

The paper is organized as follows: Section 2 describes related work and provides an overview of the proposed screening algorithm. Methods to detect lungs and ribs are described in Section 3. Sample results are shown in section 4, followed by a discussion of immediate and long-term next-steps in Section 5.

II. A Software System for Diagnosing Abnormalities in Chest Radiographs

A. Related work

Over the past decades various research efforts have focused exclusively on detection of ribs. One of early attempts was made in [2] where a method for detecting ribs contours using Laplacian gradient operators and parabolic curves is described.

In [3] researchers use vertical sections to find rib border candidates and then attempt to fit curves. Hough transform

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with parabolic curves are used to approximate rib contours in [4]. Candidate contours are then refined using Active Contour method. In [5] a method using cross variance values with 16 oriented templates is used to detect rib borders. To further improve the edges they used Hough transform and parabolic curves.

Canny edge detector was used to detect rib borders candidates [6] using a set of rules and parabolic curves. In [7] a 2-pass statistical classification method is used to detect rib pixels. In the first pass grayscale image features are used to perform an initial segmentation. In the second pass, image features and context features (neighboring structural information) are combined to reclassify each pixel.

In [22] an approach is utilized based on a massive-training artificial neural network (MTANN). In [21] the authors use a very interesting approach based on vertical and horizontal profiles in chest images. Shift-variant sinusoidal function is used as a mathematical model to detect the inter-rib spaces.

Finally, in [8] a series of gray levels calculations lead to extracting rib border candidates. Parabolic curves are, again, used to produce the final results.

It is clear from above that all approaches use pixel-based methods. Most of them ([1]-[5], [7]) use knowledge-based methods such as parabolas and curve fitting that offer significant help in identifying ribs. Use of parabolic functions to define the rib borders is indicative of the challenge of detection of the rib borders since these edges tend to be weak and often blend with the background. .

As described in Section 3, we take a different structure-based approach to the problem of rib detection. This offers two advantages: a) smaller complexity; and b) lower sensitivity to noise. To achieve a structure-based method we used wavelets, which offer simultaneous localization of spatial and frequency information.

B. Screening System Overview

High level steps in the proposed screening system are as follows:

1. *Detect lung fields.*
2. *Identify anatomical structures of interest: ribs, heart, etc.*
3. *From remaining lung field region extract image features relevant to TB detection.*
4. *Input features to 2-class classifier to output 'NORMAL' or 'ABNORMAL' label for image.*

Our approach simplifies the problem by detecting gross anatomy of interest (lung fields) and next we identify spatially collocated anatomical structures (i.e. ribs, heart), and finally we apply classification methods to identify specified abnormalities within these regions of interest. We present results from the first two stages of this process.

III. METHODS

A. Extraction of Lung Fields and Ribs

Locating organs automatically in chest radiographs is an important task for the reasons described below:

a) *Bone deterioration can be caused by cancer or other abnormality [4], [10]*
b) *Shape irregularity can highlight some serious diseases (i.e. myocardial hypertrophy)*
c) *Improving examination quality while reducing examination time*
d) *Storing and retrieving anatomical structures for reference and comparison*

The major organs contained spatially inside or in the vicinity of lung fields are heart, ribs, pulmonary aorta and clavicles. A challenge for automatic detection of the anatomy is the weak edges and overlapped structures.

In developing algorithms it is critical to consider an adequate balance of computational speed and efficiency. Since edges are hard to distinguish pure pixel-based approaches are more likely to fail since they suffer from high noise levels. With wavelets, however, solid regions of interest can be extracted with accuracy and be used to further improve edge detection. Log Gabor wavelets were found to be adequate to the task. The human visual system performs hierarchical edge detection at multiple levels of resolution and wavelet transforms perform a similar analysis [11], [12]. Wavelet filtering decomposes an image, which in case of digital CXRs is a 2D signal, into various components of different degrees of detail. In a sense there are image components that carry more information about larger and meaningful regions and other components that have information about the detailed structures such as the region edges. Our detection scheme is presented in Figure 1.

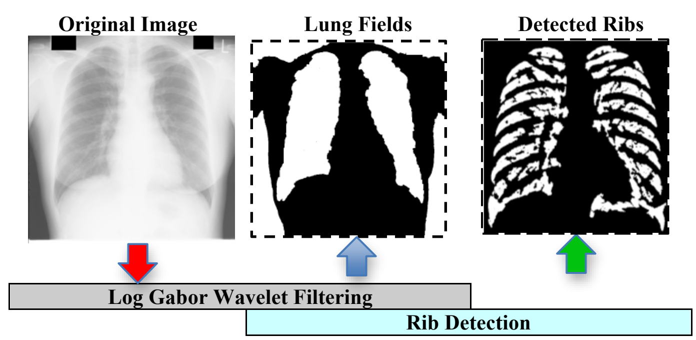

Figure 1. Proposed scheme to extract lung fields and ribs. Rib regions candidates are detected by re-tuning Log Gabor filters and using the lung fields as a mask.

As shown in figure 1, the original radiograph image is input to the log Gabor Wavelet filter component that is tuned to extract large well-defined regions such as lung fields. Then the wavelets are easily re-tuned to detect smaller structures, such as ribs, with specific orientation (~45^o for right lung field and ~135^o for left lung field) and high level of edge detail. This approach unifies segmentation of both the lung fields and the ribs.

B. Log Gabor Wavelets

Gabor filters have been widely used in image processing over the past two decades. In [13] Daugmann and in [14] Webster and De Valois showed that Gabor wavelet kernels have many common properties with mammalian visual cortical cells. These properties are orientation selectivity, spatial localization and spatial frequency characterization. In this sense, Gabor filters offer the best simultaneous localization of spatial and frequency information [15].

However, while Gabor filters are very successful they suffer from bandwidth limitation. To obtain as larger spectral information while maintaining maximum spatial localization Log Gabor filters have been introduced. Log-Gabor filters have a response that is Gaussian when viewed on a logarithmic frequency scale instead of a linear one like Gabor filters. Log-Gabor filters can be constructed with arbitrary bandwidth and the bandwidth can be optimized to produce a filter with minimal spatial extent [15]. In [16] Field defines Log-Gabor filter as:

$$G(w) = e^{-\frac{[\log(\frac{w}{wo})]^2}{2[\log(\frac{w}{wo})]^2}}$$

where w_o is the filter's centre frequency. The transfer function of the Log Gabor function is shown in Figure 2.

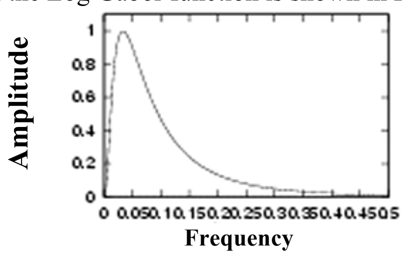

Figure 2. Log Gabor Transfer function on linear frequency scale

Log Gabor functions have two (2) important features:

a) *Have no DC component*
b) *Have an extended tail at the high frequency*

Feature a) enables the design of filters in quadrature pairs whereas the transfer function of Gabor filters is the sum of two Gaussians centered at plus and minus the centre frequency, thus resulting in a nonzero DC component.

Feature b) is the most important advantage of log Gabor filters. Field in [16] showed that since log Gabor filters have extended tails on the high frequencies are able to encode natural images more efficiently than Gabor functions which suppress higher frequency components and thus image details. Finally, Field concludes that log Gabor filter resemble the human visual system that has symmetric cells response on the logarithmic frequency scale.

C. Further steps to help identify rib structures

Before applying wavelet filtering for segmentation it is crucial that the input x-ray image is contrast-adjusted to minimize overexposure or underexposure artifacts [17]. A quick method to address this issue is to apply histogram equalization. After experimentation we found the contrast-limited adaptive histogram equalization (CLAHE) method proved to be effective. The output from applying log Gabor filtering at 45^o and 135^o orientation consists of edge fragments. The reason for these fragments is that the structures have different orientations and/or different brightness resulting from other anatomy, such as nodules, vessels, air, etc. In order to improve the output morphological operators are applied at same orientations.

Next we use the edge detector scheme proposed in [18]. A kernel of 7 coefficients is created in the Fourier domain to compute the 1^{st} and 2^{nd} derivatives. The results are more accurate than regular gradient operators, especially on detecting edges that are at non-vertical or non-horizontal angles. The reason for applying this edge detector on the original histogram-equalized image was to find possible edges on the direction of the ribs that could have been missed with the wavelet filtering. The result is coupled with the outcome of the wavelet filtering to improve the rib borders.

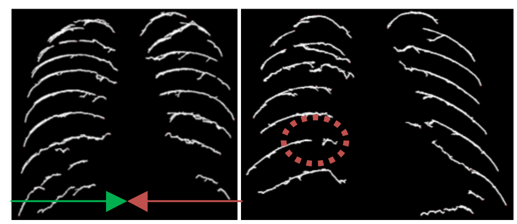

Figure 3. Two cases of rib edges detection. A broken rib border is shown in the red circle. Arrows show the direction of applying merging rule.

As shown in Figure 3 there are some ridges of the rib borders that are not connected together. We therefore apply a simple rule to merge any broken ridges: starting from the outer lung space and scanning inwards (green arrow and red arrow show direction of ridges scanning in right lung field and left lung field respectively), if two ridges are close enough and at same orientation range they are merged.

D. Edge oscillation for detecting final rib borders

In this paragraph we describe the final steps to find the rib structures. As shown in Figure 3, a log Gabor filtering can results in fragmented rib structures. However applying a simple oscillation approach we can merge the rib border candidates (Figure 4).

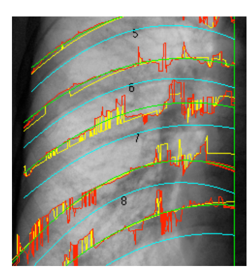

Figure 4. Oscillating approach to merge rib fragments

From each candidate (cyan) the log-Gabor filtering output is scanned on both vertical directions (90^o and -90^o) until edge pixels are found. Yellow lines correspond to edges found from border candidate at 90^o while red lines at -90^o. The two lines are averaged and the whole process is repeated to find the lower rib edge (cyan lines). This oscillating process is repeated until all lines converge and no significant change takes place (green line and cyan line). Convergence happens pretty fast: usually after 3 iterations.

There are two advantages with this approach. One is that the edge lines auto-correct themselves after a small number of iterations and secondly the parabolic curves used to describe the initial candidates are not necessarily used to identify the final rib borders. Instead, our software offers the option to smooth the detected edges using Savitzky-Golay filter [19] which is the closer to the real borders than parabolic curves. This polynomial regression filtering has the advantage to preserve the shape of the signal by maintaining relative maxima and minima.[15]

IV. RESULTS

Since ribs do not exhibit a clear border it is challenging to have a ground objective truth. We are working on developing a thorough evaluation scheme that combines subjective and objective metrics by taking into consideration the overall expert user satisfaction, and the the objective quality parameters in the detection of individual rib structures, respectively. We are presenting visual results of the proposed scheme in Figure 5. A publicly available data set [9] was used in the experiments.

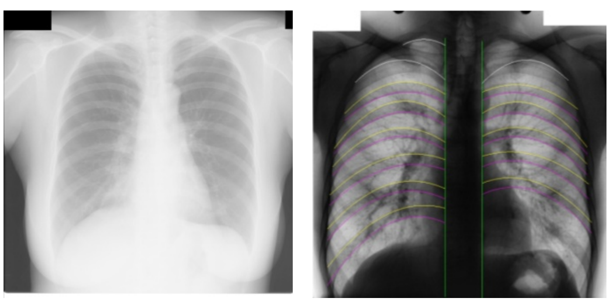

Figure 5. A chest x-ray with detected ribs after lung field extraction. Detected ribs are shown with yellow its top border and purple in its lower border output from parabolic approximation.

From figure 5 one can see that the method performs very well, sometimes even in cases where the ribs are not easily distinguishable in unprocessed images. At this point we are excluding clavicles, shown as white edges in the figure, from the scheme because of their different orientation compared to ribs. However, their identification remains a goal in our next steps.

V. CONCLUSIONS & DISCUSSION

In this paper we presented a method for detecting the lung and the rib structures on chest x-rays. This is part of an ongoing effort to develop a sophisticated system to identify abnormalities in chest x-rays.

From scientific point of view, compared to other research efforts, there are three strong points that stand out:

a) *Use of log Gabor wavelets that inherently take into consideration the orientation of structures*
b) *Unification of methods for detection of different anatomical structures such as lung fields and ribs and later pulmonary aorta, heart, etc.*
c) *Use of a smoothing technique to create the final rib borders instead of relying on parabolic functions*

Feature a) is important because instead of having a whole detection scheme rely on pixels we focus on the energy aspect of the anatomical structures. Although log Gabor filtering proved to be promising we would like to examine other wavelet families that are more sensitive to orientation and therefore more efficient, e.g. curvelets [20].

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