INVOLUNTARY DETECTION OF TUBERCULOSIS USING ACTIVE EEMERGENCE MODEL (AAM) IN CHEST RADIOGRAPHS

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***Abstract* --- Tuberculosis is one of the major diseases in the world. In this project it shows how to discriminate between normal and abnormal CXRs with manifestations of TB, using image processing techniques. In Existing System pixel based or rule based methods used extract the Lung Region, this segmentation is slow and unreliable. In our proposed system Active Adaptive Model (AAM) training and Active Adaptive Model Segmentation is been used 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: i) a content-based image retrieval approach for identifying training ii) Texture model created by warping input CXR and training CXR iii) extracting refined lung boundaries using a graph cuts optimization approach with a customized energy function. Minimize the pixel difference between the model image and target image optimization using AAM model.**

***Index Terms* – Computer-aided detection and diagnosis, lung pattern recognition and classification, segmentation, tuberculosis(TB), X-ray imaging.**

1. Introduction

Tuberculosis (TB) is the second leading cause of death from an infectious disease worldwide, after HIV. With about one-third of the world's population having latent TB, and an estimated nine million new cases occurring every year, Tuberculosis is a major global health problem. Tuberculosis is an infectious disease caused by the bacillus Myco bacterium tuberculosis, which affects the lungs. It spreads through the air when people with active TB cough, sneeze, or otherwise expel this infectious bacteria. TB is mostly found in sub-Saharan Africa and South east Asia, where wide spread poverty and malnutrition reduce resistance to this disease. Moreover, opportunistic infections inimmune-compromised HIV/AIDS patients have exacerbated this problem. The increasing appearance of multi-drug resistant TB has created an urgent need for a cost effective screening technology to monitor progress during treatment.

For treating TB there are many existing antibiotics. While mortality rates are so high when left untreated, treatment with anti biotics greatly improves the chances of survival. Unfortunately, diagnosing TB is still a major problem. The definitive test for Tuberculosis is the identification of Mycobacterium tuberculosis in a clinical sputumorpus sample, which is the current gold standard. However, it may take many months to identify this slow-growing organism in the lab. Another method is sputumsmear microscopy, in which bacteria in sputum samples are observed under a microscope. This method was developed more than 100 years ago. In addition, several skin tests based on immune response are available for identifying whether an individual has contracted TB. However, skin tests are not reliable always. The latest developments for detection are molecular diagnostic tests that are very fast and accurate, and that are highly sensitive. However, further economic support is Required for these tests to become common place. In this paper, I present an automated approach for detecting Tuberculosis manifestations in chest X-rays (CXRs) in lung segmentation and lung disease classification. An automated approach to X-ray reading allows mass screening of very large populations that could not be managed manually. Apostero-anterior radiograph (X-ray) of a patient's chest is a major part of every evaluation for Tuberculosis. The chest radiograph includes all thoracic anatomy and provides a very high yield, given the low cost and single source. Therefore, almost reliable screening system for Tuberculosis detection using radiographs would be a major critical step towards more powerful Tuberculosis diagnostics.

Figure 1: Examples of normal CXRs in the MC dataset

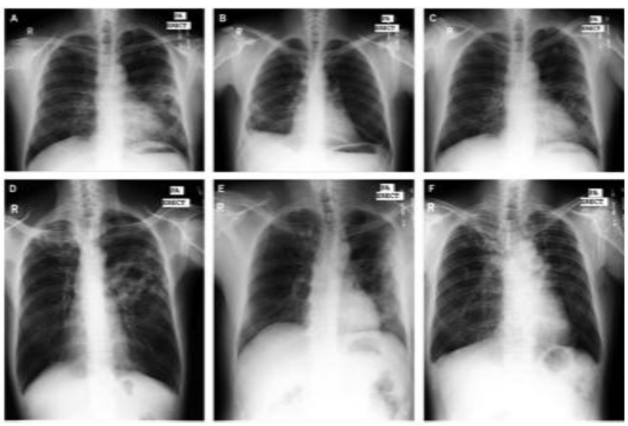

Figure2: ExamplesofabnormalCXRsintheMC dataset.

Fig.1shows examples of normal CXRs without signs of TB These examples are from Montgomery County (MC)dataset. Fig.2shows positive examples with manifestations of Tuberculosis, which are from the same dataset. Typical manifestations of TB in chest Xrays are, infiltrations, cavitation, effusions, armillary patterns. For instance, CXRA andCinFig.2 have infiltrates in both lungs. CXRB is a good example of pleural TB, which is indicated by the abnormal shape of costophrenic angle of the right lung..

In CXRD the irregular infiltrates in the left lung with a large area of cavitation. There is scarring in the right apical region. CXRE shows the peripheral infiltrates in the left lung. Finally,CXRF shows TB scars resulting from an older Tuberculosis infection.In this paper describes how to discriminate between normal and abnormal CXRs with manifestations of Tuberculosis, using image processing techniques. This paper presents the AAM set segmentation method for the lung segmentation AAM Sets are an important category of modern image segmentation techniques are based on partial differential equations(PDE),

i.e.progressive evaluation of the differences among neighboring pixels to find object boundaries. The AAM set method was initially proposed to track moving interfaces. It can be used to efficiently address the problem of curve/surface/etc. Initial contour is taken over the object that time the AAM will be zero then this contour is moving towards the object boundary then it settled own in the boundary of the object well. First take the outside contour. Then move towards the object. If the gray AAM changing, move it else not. Stop when gray AAM changes.

2. Related Works

The invention of the possibility of digital image processing and digital chest radiography has given new impetus to computer aided screening and diagnosis. Still the standard CXR is a very complex imaging tool despite of its omnipresence in medical practice. In the last 10years ,several ground-breaking papers have been published on computer aided diagnosis(CAD)inCXRs.However,there is no doubt that more research is needed to meet the practical performance requirements for deployable diagnostic systems. In are cent survey, vanGinneken*etal*. State that 45 years after the initial work on computer aided diagnosis in chest radiology, .Automated nodule detection is becoming one of the more mature applications of decision support/ automation for CXR and CT.Several studies have been published evaluating the capability of commercially available CAD systems to detect lung nodules. The result is radiologists in diagnosing lung cancer.However only one of many manifestations of TB in radiographs represents the nodules.In recent years,due to the complexity of developing full-fledged CAD systems for X-ray analysis, research has concentrated on developing solutions for specific sub problems, the segmentation of the lung field is a typical task that any CAD system needs to support for a proper evaluation of CXRs. Other segmentations that may be helpful include the segmentation of the ribs, heart, and clavicles. For example, vanGinneken*etal.* Compared various techniques for lung segmentation, including active shapes, rule-based methods, pixel classification, and various combinations thereof. Their conclusion was that pixel classification provided very good performance on their test data. Dagwood presented an iterative segmentation approach that combines intensity information with shape priors trained on the publicly available JSRT database.

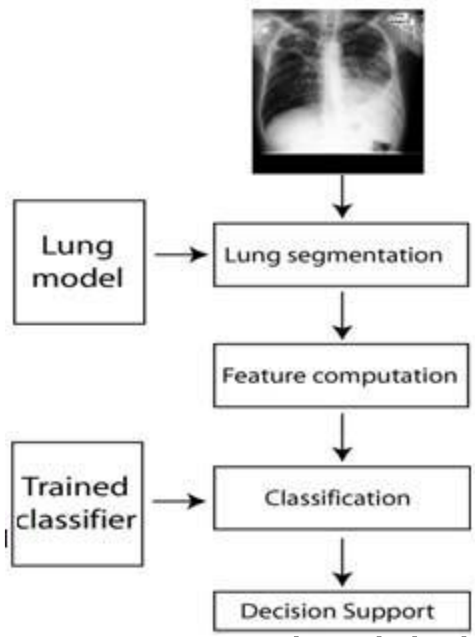

Figure 3: CXR and its calculated lung

model Different feature types and ways to

aggregate them have
Been reported in the literature depending on the lung segmentation. For example, vanGinneken*etal.* Subdivide the lung into overlapping regions of various sizes and extract features from each region. The use the moments of responses to a multi scale filter bank is used to detect abnormal signs of diffuse textural nature. In addition, they use the difference between corresponding regions in the left and right lung fields as features. A separate training set is constructed for each region and final classification is done by voting and a weighted integration.

3. Method

This section presents the implemented lung segmentation methods, feature computation ,and classification. Fig.3 shows the architecture of our system with the different processing steps, which the following sections will discuss in more detail. First, our system segments the lung of the input CXR using a graph cut optimization method in combination with a lung model. Our system then computes a set of features as input to a pre-trained binary classifier for the segmented lung field,. Finally, using decision rules and thresholds, the classifier outputs its confidence in classifying the input CXR as a TB positive case, for example.

3.1AAMSetSegmentation Method

Lungsegmentationismodeledasanoptimizationproblemthattakespropertiesoflungboundaries,regions,andshapesintoaccount.Ingeneralitcanbeexplainedassegmentationinmedicalimageshastocopewithpoorcontrast,acquisitionnoiseduetohardwareconstraints,andanatomicalshapevariations.Lungsegmentationisnoexceptioninthisregard. AAM set segmentation algorithm as follows:

1.Taking the chest image

2.Using graph gut segmentation algorithm segment only region of the Lung from the background

3.Taking the special characteristics of the image is known as

Feature extraction. The following features are extracted:

Intensity histograms (IH).

Gradient magnitude histograms(GM)

Shape descriptor histograms (SD), Shape features,

classifier, It is used to classify the different kind of data

with the help of training feature extracted data. Here we

are using SVM classifier to classify the input data

Input Output Normal/Affected

Training Feature Data (Data Base)

An important category of modern image segmentation techniques that are based on partial differential equations (PDE) are AAM Sets. PDE is the progressive evaluation of the differences among neighboring pixels to find object -boundaries. The AAM set method was initially proposed to track moving interfaces. It can be used to efficiently address the problem of curve/surface/etc. Initial contour is taken over the object that time the AAM will be zero then this contour is moving towards the object boundary then it settle down in the boundary of the object well.

1. Take the outside contour
2. Move towards the object
3. If gray AAM changing move it else not
4. Stop when gray AAM changes

This implementation is based on following PDE update:

B. Features

I experimented with two different feature sets to describe
normal and abnormal patterns in the segmented lung field.
The motivation is to use features that can pick up subtle
structures in a CXR.

1) Object Detection Inspired Features

Set A: As the first set, I use features that I have been successfully applied to microscopy images of cells for which I classified the cell cycle phase based on appearance patterns. It is the same set that is used in our earlier TB classification work. This set is versatile and can also be applied to object detection applications for example the first set is a combination of shape, edge, and texture descriptors. For each descriptor, first an histogram is computed that shows the distribution of the different descriptor values across the lung field. Each histogram bin is a feature, and all features of all descriptors put together form a feature vector that are input to our classifier. Through empirical experiments, it is found that using 32 bins for each histogram gives good practical results. The following shape and texture descriptors are used,• Intensity histograms (IH).

• Gradient magnitude histograms (GM).

• Shape descriptor histograms (SD)

2) CBIR-Based Image Feature

Set B: For the second feature set, Set B, I use a group of low AAMfeatures motivated by content-based image retrieval
(CBIR). This feature collection includes intensity, edge, texture and shape moment features, which are typically used
by CBIR systems. The entire feature vector has 594dimensions, which is more than three times larger than the
feature vector of Set A, and which allows to evaluate the effect of high dimensional feature spaces on classification accuracy. Then extract most of the features, except for Hu moments and shape features, based on the Lucene image retrieval library. The Feature Set B contains the following features.

Tamura texture descriptor: The human visual perception is the motivation of the Tamura descriptor. The descriptor comprises a set of six features. Only three of these features are used in our method, which have the strongest correlation with human perception: contrast, directionality, and coarseness.CEDD and FCTH: CEDD (color and edge direction descriptor) and FCTH (fuzzy color and texture histogram)incorporate color and texture information in one histogram. They differ in the way they capture textureinformation.Hu moments: These moments are mainly used in image analysis. They are invariant under image scaling, translation, and rotation. The DISCOVIR system(distributed content-based visual information retrieval) is
used to extract Hu moments.CLD and EHD edge direction features: CLD (color layout descriptor) and EHD (edge histogram descriptor)are MPEG-7 features. CLD captures the spatial layout of the dominant colors on an image grid consisting of 8* 8blocks and is represented using DCT (discrete cosine transform) coefficients. EHD represents the local edge distribution in the image, i.e., the relative frequency of occurrence of five types of edges (vertical, horizontal, 45diagonal, 135 diagonal, and non-directional) in the subimages.

Primitive length, edge frequency, and autocorrelation:These are a well-known texture analysis method that uses statistical rules to

describe the spatial distribution and relation of gray values.Shape features: A collection of shape is used features
provided by the standard MATLAB implementation(region props), such as the area or elliptical shape features of local patterns

C. Classification

The proposed system uses a support vector machine (SVM)
to detect abnormal CXRs with TB, which classifies the computed feature vectors into either normal or abnormal. An
SVM is a supervised non-probabilistic classifier in its original form that generates hyperplanes to separate samples from two different classes in a space with possibly infinite dimension. The unique characteristic of an SVM is that it does so by computing the hyperplane with the largest margin; i.e., the hyperplane with the largest distance to the nearest training data point of any class. Ideally, the feature vectors of abnormal CXRs will have a positive distance to the separating hyperplane, and feature vectors of normal CXRs will have a negative distance. The larger the distance the more confident in case of the class label. Therefore use these distances as confidence values to compute the ROC curves.

4. Conclusion

An automated system that screens CXRs for manifestations of TB has been developed. When given a CXR as input, the proposed system first segments the lung region using an optimization method based on level set method. This method combines intensity information with personalized lung at lasmodels derived from the training set. We compute a set of shape, edge, and texture features as input to a binary classifier, which then classifies the given input image into either normal or abnormal. In this paper, I compare two different established feature sets: one set specially used for object recognition and the other used in a system that can assist radiologists and public health providers in the screening and decision process. These comparison results have encouraged to test the system in the field under realistic conditions. In future experiments, it will evaluate our system on larger datasets that we will collect using our portable scanners

References

[1] S. Candemir, S. Jaeger, K. Palaniappan, S. Antani, and G.
Thoma ,"Automatic Tuberculosis screening using chest
radiographs,"in IEEE Medical imaging,vol. 33,February
2014.

[2] World Health Org., Global tuberculosis report 2012.

[3] World Health Org., Global tuberculosis control 2011
2011.

[4] Stop TB Partnership, World Health Org. , The Global
Plan to Stop TB 2011–2015 2011

[5] S. Candemir, S. Jaeger, K. Palaniappan, S. Antani, and G.
Thoma,"Graph-cut based automatic lung boundary
detection in chest radiographs," in *Proc. IEEE Healthcare Technol. Conf.: Translat. Eng.Health Med.*,
2012, pp. 31–34.

[6] S. Candemir, K. Palaniappan, and Y. Akgul, "Multi-class
regularization parameter learning for graph cut image
segmentation," in *Proc.Int. Symp. Biomed. Imag.*, 2013, pp. 1473–1476.

[7] S. Jaeger, A. Karargyris, S. Antani, and G. Thoma,
"Detecting tuberculosis in radiographs using combined
lung masks," in *Proc. Int. Conf.IEEE Eng. Med. Biol.
Soc.*, 2012, pp. 4978–4981.

[8] C. Leung, "Reexamining the role of radiography in
tuberculosis case finding," *Int. J. Tuberculosis Lung
Disease*, vol. 15, no. 10, pp. 1279–1279, 2011.

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