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# SEGMENTATION OF CHEST RADIOGRAPHS INFECTED BY TUBERCULOSIS USING GRAPH-CUT

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**Abstract**

Fight against human immunodeficiency virus (HIV) is difficult without dealing the problems associated with difficult diagnosis of Tuberculosis (TB), a deadly infectious disease. When left untreated, the mortality rates of the patients with tuberculosis are high. The presence of cavities in the upper lung zones is indicates that the disease has developed into a highly infectious state. Chest radiographs play an important role in the detection and diagnosis of diseases related to lungs. Standard diagnostics still rely on methods developed in the last century that are slow and often unreliable. This paper presents an improved approach for detecting tuberculosis in conventional postero-anterior Chest X-Rays (CXRs). We extract the lung region using graph-cut segmentation for which the optimal weights are determined.

**keywords:**Chest Radiographs, Histogram Equalization, Graph-Cut Segmentation.

## I. INTRODUCTION

Tuberculosis commonly referred to as TB is an infectious disease caused by the bacillus Mycobacterium tuberculosis typically affecting the lungs (pulmonary TB). But it can affect other sites as well (extra-pulmonary TB). In 2013, about 6.1 million cases of TB were reported to WHO (World Health Organization). Of these, nearly 5.7 million were newly diagnosed and another 0.4 million were already on treatment. TB ranks as the second leading cause of death worldwide. Between 2000 and 2013, an estimated number of 37 million lives were saved through effective diagnosis and treatment. Though fatality rate has been highly reduced, TB still poses a threat in developing countries like sub-Saharan Africa and Southeast Asia. Diagnosis relies on Chest X-Rays which is the primary detection tool.

Candemir [1] explained about the use of non-rigid registration driven robust lung segmentation method for the automatic detection of the lung regions by implementing this technique over two datasets namely – Montgomery Country (MC) Chest Radiographs (CXRs) and Japanese Society of Radiological Technology (JSRT). Anup [2] took a hybrid knowledge-based Bayesian classification approach to detect TB cavities automatically. For classification purpose, he had made use of gradient inverse coefficient of variation and circularity measures. Stefan [3] for the purpose of segmentation utilized three different masks viz. the intensity mask, the lung model mask and the Log Gabor mask. The CXRs were classified as normal and abnormal by Support Vector Machine (SVM) classifier. Two datasets of conventional posterior-anterior (PA) CXRs, MC and JSRT were used. But this method could be applied only to static model alignment. Clark [4] in 2011 applied step-wise binary classification over development specimen database and independent specimen database obtained from National Health Laboratory Systems (NHLS). Palaniappan [5] detected the anatomical boundaries using energy minimization-based algorithms and classified using multi-class boosting algorithm for the JSRT medical images. Thoma [6] had segmented the CXRs by fusing shape information with Active Shape Model (ASM) in the final stage. He utilized maximum amount of information available to him. He detected the outline of clavicles for 247 CXRs that were available to him. For the available medical images, Freedman [7] removed the surrounding bone regions using bone suppression and soft tissue visualization algorithm. He also detected the actionable nodules and for analysis implemented Localized Receiver Operating Characteristic (LROC).

Sameer [8] applied graph-cut based lung segmentation to the MC set in two stages: i) average lung shape model calculation and ii) lung boundary detection. In order to segment the cavity and to extract the features, Xu [9] combined a 2-D Gaussian-model-based Template Matching (GTM) along with Hessian-matrix-based Image Enhancement (HIE) in order to achieve higher accuracy. Clara [10] segmented the clavicles automatically for PA CXRs by combining three different methods namely, ASM segmentation, pixel classification and dynamic programming. Hogweg [11] in 2005 combined textural abnormality detection system and clavicle detection system for the pixel classification of CXRs obtained from The Netherlands. In [12], initially a statistical model was extracted by the author, followed by the optimization of iterative thresholding for segmenting the images and ASM technique was used in the later stages for the publicly available database. Shi [13] has utilized a modified scale-invariant feature transform (SIFT) local descriptor in order to characterize the image features and a deformable model to adapt to the shape variability of different patients. Maes in [14] proposed minimal shape and intensity cost path segmentation algorithms that optimize for shape and intensity characteristics. This algorithm validated well for segmentation of anatomical features of chest and hand radiographs. Ginneken [15] applied ASM for segmentation and texture analysis schemes for the PA CXRs obtained from The Netherlands but it did not work well for all abnormal cases. Ojala [16] implemented multi-resolution approach to gray scale and rotation invariant texture classification based on local binary patterns (LBP). It was preferred because it could be applied to any kind of medical image and also for its computational simplicity.

## II. DATASET

The standard digital image database for Tuberculosis has been created by the National Library Of Medicine (NLM) in collaboration with the Department of Health and Human Services, Montgomery County (MC), Maryland, USA. The dataset was de-identified by the data providers and were exempted from IRB review at their institutions [17], [18]. The data set use and public release were exempted from IRB Review (No. 5357) by the NIH Office of Human Research Projections Programs. The set contains data from X-Rays collected under Montgomery County`s Tuberculosis screening program. The MC set contains 138 PA CXRs in total of which 58 CXRs are abnormal with manifestations of TB and 80 CXRs are normal. For this set, the ground-truth radiology reports are known which have been confirmed by clinical tests. A wide range of TB-related abnormalities have been covered by the abnormal CXRs including miliary patterns and pleural effusions.

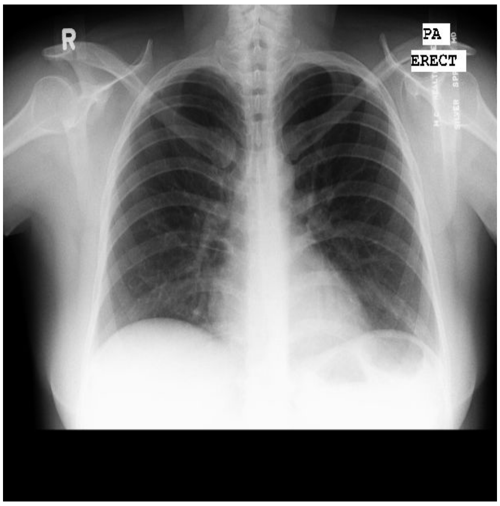


**Figure 1. Chest X-ray of a normal person (NLM Montgomery CXR Set)**

All CXR images have a matrix size of 4020 x 4892 and the number of gray levels is 12-bits. Figure 1 shows the CXR of a normal person (i.e.) a person not infected by TB. This image is subjected to further processes in our proposed system.

## III. METHODS

According to the proposed system, the input image is pre-processed in order to remove unwanted information such as noise, which is then subjected to segmentation process. Later various descriptors are found for the same.

***A) Pre-processing***

Before the proposed technique is applied, every image in the MC set is pre-processed. There are a great number of pre-processing techniques available. Of these, background subtraction and histogram equalization techniques are being employed in this paper. Background subtraction, also popularly referred to as Foreground Detection, is an important technique in the fields of image processing [15] and computer vision wherein an image's foreground is first extracted for further processing. A foreground object can be described as an object of attention which helps to reduce the amount of data to be processed as well as provide important information to the task under consideration. Background subtraction extracts the shape of a desired object, provided the object intensity/color is sufficiently different from the background. It is sensitive to changing illumination and undesired movement of the background (for example, trees blowing in the wind, reflections of sunlight off of cars or water).

Histogram equalization is generally implemented for contrast adjustment making use of the image's histogram. This method increases the contrast of images, especially when the usable data of the image is represented in terms of close contrast values. The intensity of the images can be better distributed evenly on the histogram. This helps areas of lower local contrast to gain a higher contrast. [11] Histogram equalization accomplishes this task by effectively spreading out the most frequent intensity values. The method is useful in images where both background and foreground are bright or both are dark. In particular, this method can lead to better views of bone structure in x-ray images. Histogram equalization can sometimes result in undesirable effects (like visible image gradient) when applied to images with low color depth.

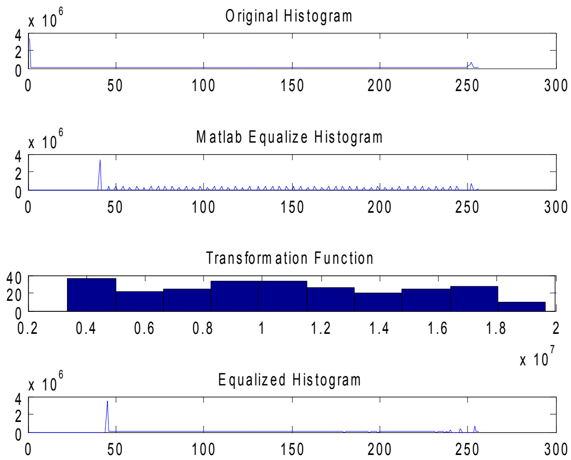


**Figure 2 Histogram Equalization of the input CXR**

***B) Segmentation***

Segmentation, an important part of image analysis refers to the process of partitioning an image into multiple segments. Image segmentation is the process by which a label is assigned to every pixel in an image such that pixels with the same label share certain visual characteristics. The goal is to simplify and change the representation of an image. Segmentation is useful for image editing, image compression, object recognition, or image database look-up. Segmentation by computing a minimal cut in a graph is a new and quite trending approach for segmenting images. This approach guarantees global solutions, which always find best solution, and in addition to this does not depend on a good initialization.

Graph theory is nothing but the study of graphs. A graph is a representation of a set of objects, where many pairs of the objects are connected by means of links. It is a mathematical structure and is used to model pairwise relations between objects from a certain collection. In a graph G = (V, E), V and E denote the set of vertices and edges of G, respectively. A weighted graph associates a weight with every edge in the graph.

Binary problems (e.g. denoising a binary image) can be solved in a better manner using this approach; problems where pixels can be labeled with more than two different labels (such as stereo correspondence or denoising of a grayscale image) cannot be solved exactly, but solutions produced are almost near to the global optimum [5]. The term "graph cuts" is applied specifically to models which employ a max-flow/min-cut optimization. [8] Straightforward implementation of graph cuts may even require a lot of memory for 3-D applications. It is not only effective to specific image with known information but also to the natural image without any pre-known information. For the segmentation of N-D images also, graph cut based methods are applicable. But graph cuts find the cheapest subset of edges (a cut) that separates seeds marking the inside of the object and background regions [6].

***C) Descriptors***

Three different descriptors are computed for the segmented image namely – HOG, LBP and EHD. Histogram of Oriented Gradient (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. This technique counts the occurrences of gradient orientation in localized portions of an image. This method is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy. Local object appearance and shape within an image can be described effectively with the help of distribution of intensity gradients or edge directions. The implementation of these descriptors can be achieved in a remarkable manner by dividing the image into small connected regions, called cells, and for each cell a histogram of gradient directions or edge orientations for the pixels within the cell is compiled. The HOG descriptor maintains a number of key advantages over other descriptor methods. Since the HOG descriptor operates efficiently on localized cells, this method upholds invariance to geometric and photometric transformations, except for object orientation. The HOG descriptor is thus particularly suited for human detection in images.

Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Because of its discriminative power and computational simplicity, LBP texture operator has become a most wanted approach in various applications. It can be seen as an alternative approach to the traditionally divergent statistical and structural models of texture analysis. The most significant property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes affected by illumination variations. Another noteworthy property is its computational simplicity, which makes it easy to analyze images in challenging real-time settings. LBP looks at points surrounding a central point and tests whether the surrounding points are greater than or less than the central point (i.e. gives a binary result). It has been determined that LBP along with the HOG descriptor improves the detection performance considerably on some datasets.

Edges play a vital role in our visual system, and these coefficients quantify them. The major implementation of the Edge Histogram Descriptor (EHD) is image retrieval. Though an edge may warp due to changes in viewpoint, the image information along the same edge will never appear "out of order" between viewpoints. While edges are more likely to fall on either side of the occluding boundaries, there is a simple way to deal with them: separate the domain of the support region into two parts, one on either side of the edge and develop a descriptor for each of these regions.

## IV. RESULTS AND FUTURE WORK

This section shows the practical evaluation of our proposed system. Here, the results of our segmentation process have been shown and the outcome of the descriptors are analysed for the given input image. The cluster images of Figure 3 are used for extracting the descriptors such as HOG, LBP and EHD as per the requirement of the user of the system. The descriptor will give the output only in the form of pixels.

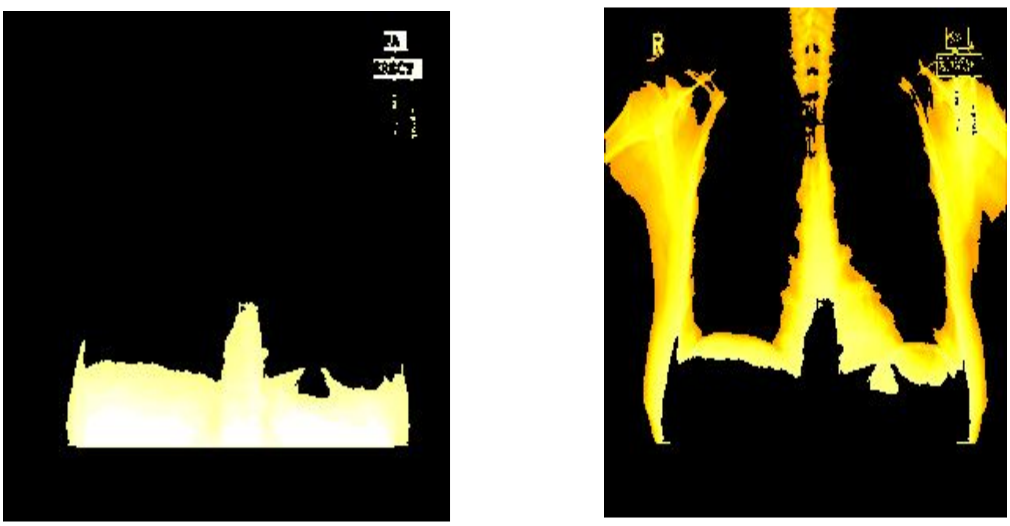

**Figure 3 The first image shows the objects in cluster1 and the second image shows the objects in cluster 2. This is the outcome of the Graph-Cut Segmentation process.**

The proposed system can be further made to undergo the process of classification as either normal or abnormal images used various classifiers such as SVM (Support Vector Machine) classifier [9]. It could also be compared with advanced segmentation techniques like Advanced-fuzzy Segmentation.

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