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A METHOD FOR DETECTION OF TUBERCULOSIS IN LUNG BY IMAGE PROCESSING

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Abstract: - Tuberculosis is one of the most dangerous health problems in the world. It mainly affects in lungs. The symptoms of Tb may vary depending on what type of tuberculosis may occur. The starting stage of disease may be symptom free, it is inactive stage. In active stage, some symptoms like slight fever, night sweat, weight loss, and fatigue will appear. In the investigating cases for suspected tuberculosis (TB), chest radiography is not only the key techniques of diagnosis based on the medical imaging but also the diagnostic radiology.

Keywords: CAD, Image processing, Tuberculosis, Segmentation, Feature Extraction, Classification.

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INTRODUCTION

Tuberculosis (TB) is an infection disease over the world population. It is commonly caused by bacteria which is known as Mycobacterium tuberculosis and mostly affected to the lungs of the human beings. TB is spread through the air from everyone or everywhere. By coughing, sneezing, spitting felt in patients, TB bacteria disperses widely into the air. In every year, one third of population of the world has been got Mycobacterium TB bacteria at a rate of one percent of population with new infection.

Large number of patients with TB infections needs to be X-rayed and screen for active TB to ensure a proper treatment of their infections [1].Taking Standard Chest X-rays (CXRs) is an inexpensive way to screen for the presence of TB. The purpose of screening system is to identify everything that is or could be related to a patient having TB infections. But mass screening of a large population is a time consuming and tedious work, which require considerable effort when done manually. For this reason, Computer-aided diagnostic systems (CAD) used to detect Tuberculosis infections in chest X-rayed. These systems have the potential to lessen the TB detection error risk and also depend on the radiologists.

The imaging features of active TB and inactive disease [3] do have some unique features, but also overlap. Within the lung, imaging features of active pulmonary TB include but are not limited to the following manifestations:

- Cavity formation, a finding in the lung with a detectible radio dense rim.
- Air space consolidation small or large that is segmental or lobar opacity in the lung.
- Miliary pattern is a fine granular sandy or seed-like appearance throughout the entirety of both lungs.
- Bronchiectasis or enlargement of airways can appear as tubular rings or cylinders of irregular diameter.

PROPOSED WORK

Initially we remove the noise from the images. For filtering the images we use the wiener filter for denoising. In a second step, we employ a graph cut approach and model the lung boundary detection with an objective function. "Graph cuts" is applied specifically to those models which employ a max-flow/min-cut optimization. After lung segmentation we extract three features such as LBP, HOG, and Tamura features are extracted. Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighbourhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity HOG counts occurrences of gradient orientation in localized portions of an image. It also computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy. And finally we extract the Tamura features. These features are given to the SVM classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. The trained classifier will predict about the CT lung images. And finally we analyze about our classifier performance with the existing system.

We present an automated approach for detecting TB manifestations in chest X-rays (CXRs), based on our earlier work in lung segmentation and lung disease classification. An automated approach to X-ray reading allows mass screening of large populations that could not be managed manually. A posterior-anterior radiograph (X-ray) of a patient's chest is a mandatory part of every evaluation for TB. The chest radiograph includes all thoracic anatomy and provides a high yield, given the low cost and single source. Therefore, a reliable screening system for TB detection using radiographs would be a critical step towards more powerful TB diagnostics.

Data Collection

The system is evaluated on a data set of frontal chest x-rays compiled by the Japanese Society of Radiological Technology (JSRT) [9]. The set contains 247 chest x-rays, among which 154 x-rays are abnormal and 93 x-rays are normal. All x-ray images have a size of 2048x2048 pixels and a gray-scale color depth of 12 bit. The JSRT set is publicly available and has ground truth masks [4] for performance evaluation of lung segmentation.

For this study, radiographs were at first imported to MATLAB environment using built-in function available in the MATLAB image processing toolbox.

Pre-processing

The main goal of the pre-processing is to improve the image the features to be extracted should be guided by the following quality to make it ready to further processing by removing or concerns: reducing the unrelated parts in the background of the x-ray images. It will prepare the x-ray for the next two-process segmentation and feature extraction [4]. The noise and high frequency components removed by filters. Pre-processing methods use a small neighbourhood of a pixel in an input image to get a new brightness value in the output image. Such pre-processing operations are also called filtration. There are obvious reasons for the need of image pre-processing:

- Improvement of image quality to meet the requirements of physician
- Noise reduction
- Contrast enhancement
- Correction of missing or wrong pixel values
- Optimal preparation of data for post processing
- Elimination of acquisition-specific artefacts

Segmentation

The graph cut algorithm models computer vision labeling problems such as segmentation and disparity estimation as energy minimization using an undirected weighted graph *G = (V,E)*. The set of vertices *V* represents the pixel properties such as intensity; and a set of edges *E* connects these vertices. The edge weights typically represent the spatial proximity measure between vertices. The graph has two special vertices (terminals) representing fg and bg labels. There are two types of edges: (i) neighborhood edges denoted as {p, q}, where p, q 2 V model the boundary properties of objects; and (ii) edges between terminals and pixels denoted as {p, S} and {p, T}, where S and T represent the fg and the bg terminals. The graph cut algorithm uses an objective function that consists of a data and a smoothness term. The data term forces the algorithm to produce a solution that is consistent with the data (e.g. image intensities). On the other hand, the smoothness term encourages the algorithm to favor a smooth solution (e.g. assigning similar labels to neighborhood pixels).The edge weights between the terminals and the pixels are integrated into the data energy term; the neighborhood edges are integrated into the smoothness energy term of the objective function. To minimize the objective function, we compute the min-cut which partitions the graph into two subgraphs such that each pixel is connected to either the S or the T terminal, and thus is either labeled as fg or bg.

Feature extraction

Histogram of oriented gradients (HOG) is a descriptor for gradient orientations weighted according to gradient magnitude [7].The image is divided into small connected regions, and for each region a histogram of gradient directions or edge orientations for the pixels within the region is computed. The combination of these histograms represents the descriptor.

Local binary patterns (LBP) is a texture descriptor that codes the intensity differences between neighboring Pixels by a histogram of binary patterns [4], LBP is thus a histogram method in itself. The Binary patterns are generated by thresholding the Relative intensity between the central pixel and its neighboring pixels. Because of its computational simplicity and efficiency, LBP is successfully used in various computer vision applications often in combination with HOG.

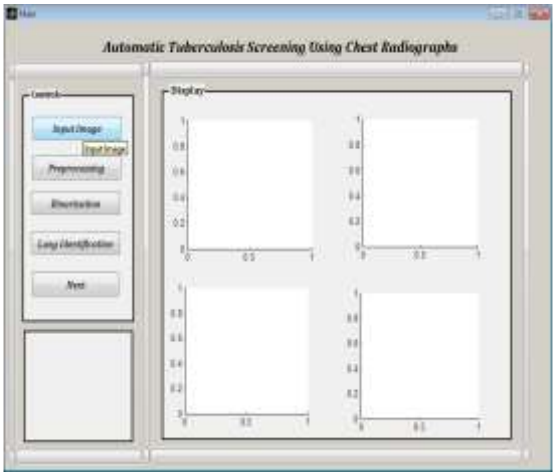
Classification

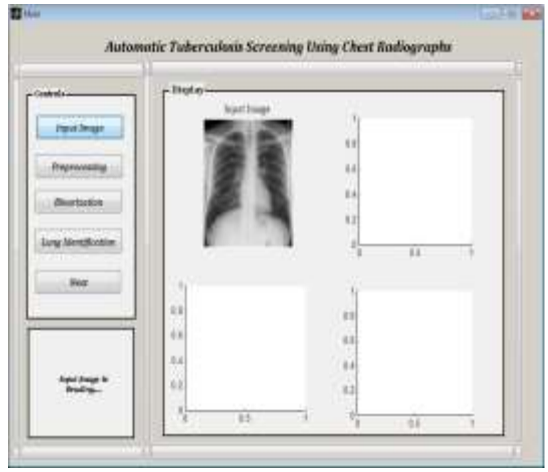
To detect abnormal CXRs with TB, here use a support vector machine (SVM), which classifies the computed feature vectors into normal and abnormal class. An SVM is a supervised non-probabilistic classifier that generates hyper planes to separate samples from two different classes in a space with possibly infinite dimension. The important characteristic of an SVM is that it classifying the data by computing the hyper plane with the largest margin. It use the hyper plane with the largest distance to the nearest training data point of any class. The feature vectors of abnormal CXRs will have a positive distance to the separating hyper plane, and feature vectors of normal CXRs will have a negative distance.

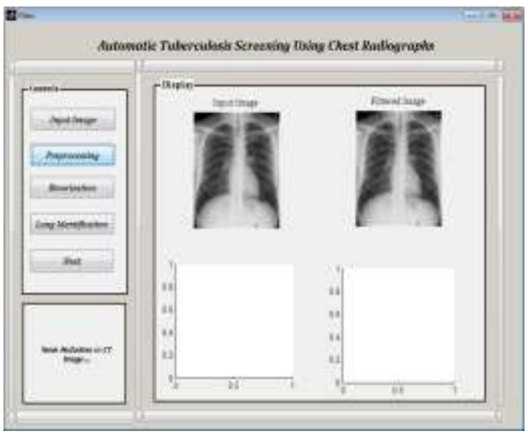
EXPERIMENTAL RESULT

We have implemented this work on MATLAB 2012b which takes nearly 18 sec to complete the detection process.

Her 1800 iteration used. When the iteration increases better result will obtain.


Automatic Tuberculosis Screening Using Chest Radiographs


Automatic Tuberculosis Screening Using Chest Radiographs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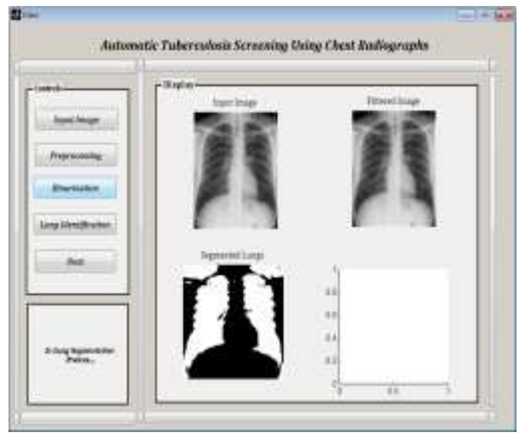
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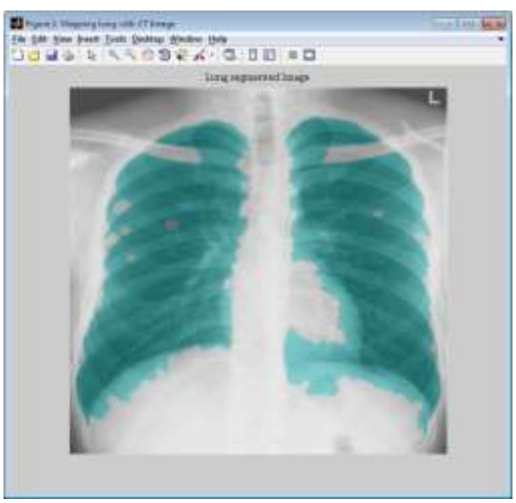
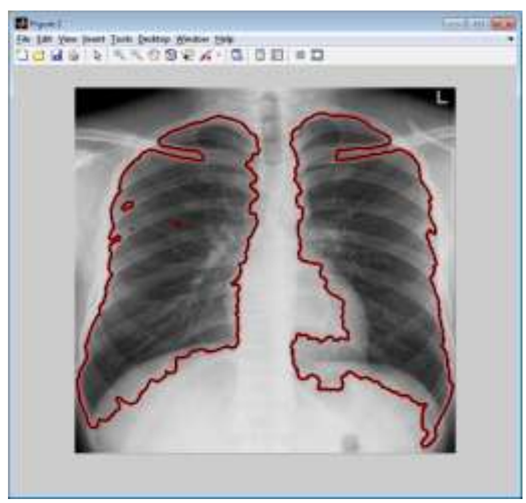
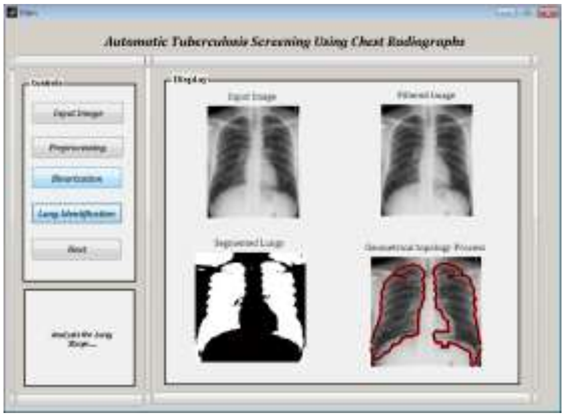
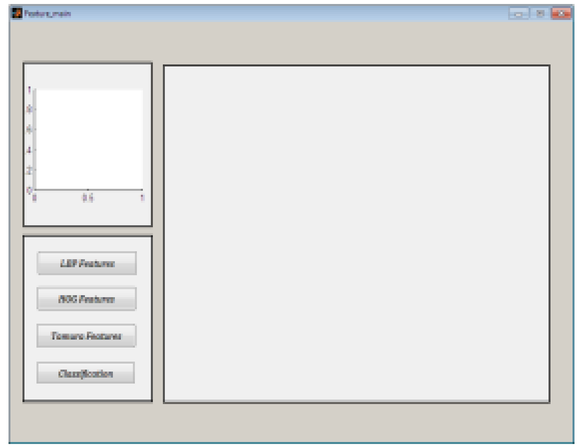
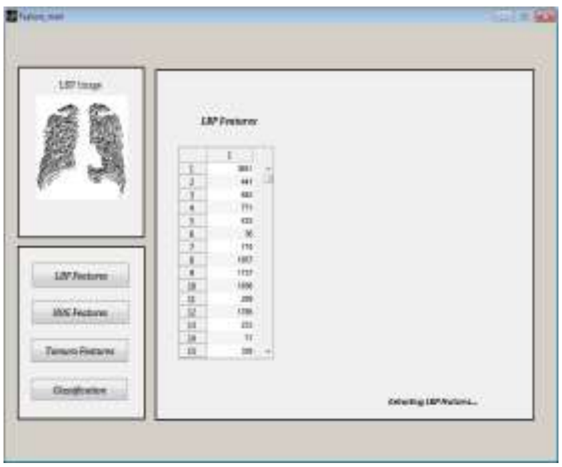
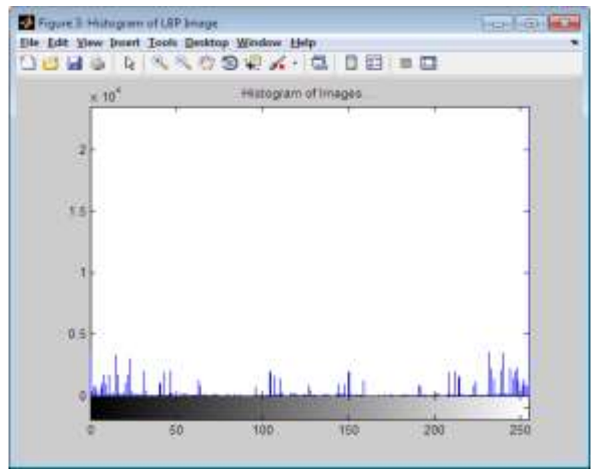





Automatic Tuberculosis Screening Using Chest Radiographs
Input Image
Filtered Image
Preprocessing
Lung Identification
Next

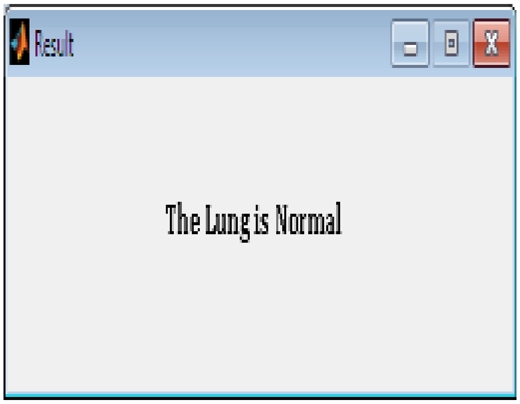

LBP Features
HOG Features
Texture Features
Classification

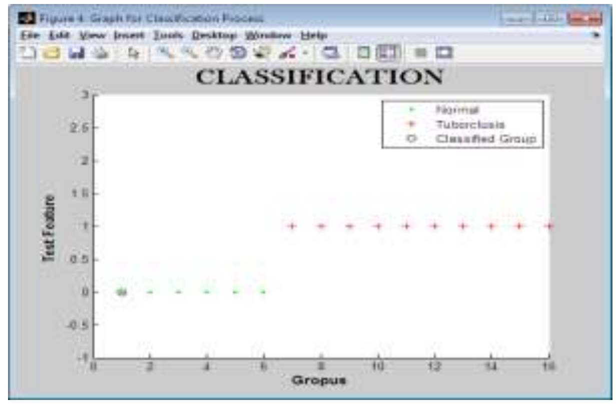

LBP Image
LBP Features
HOG Features
Texture Features
Classification

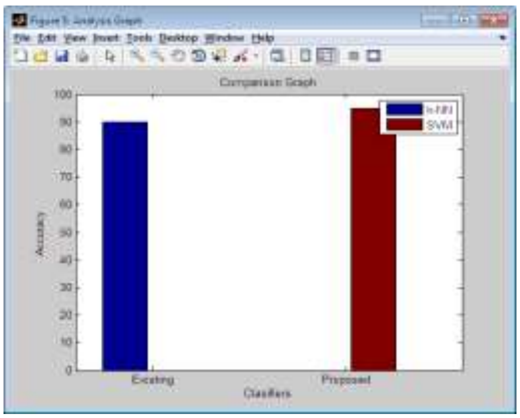

Histogram of LBP Image
File Edit View Insert Tools Desktop Window Help
Histogram of Images
0 50 100 150 200 250

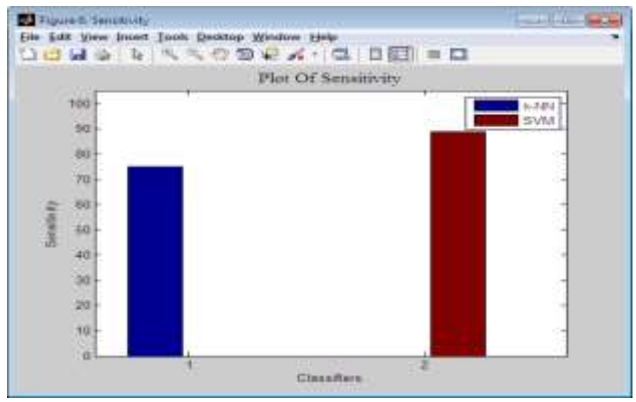

LBP Image
LBP Features
HOG Features
Texture Features
Classification

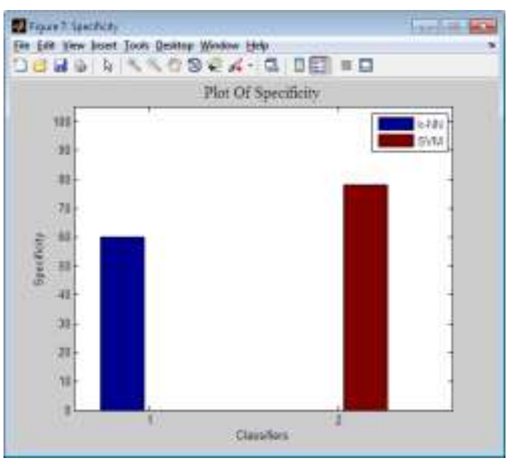

LBP Image
LBP Features
HOG Features
Texture Features
Classification











CONCLUSION

We have presented a fully automatic scheme for detection of tuberculosis in lungs using chest radiographs. The method is based on graph cut segmentation and classification using SVM. Features are extracted using LBP and HOG. Experiments were performed on a database containing chest radiographs with interstitial disease with excellent results. On a large database from a mass chest screening against TB with images with textural abnormalities, containing many subtle cases, the results were fairly accurate. The results suggest that this method may be helpful to radiologists for reading mass chest screening images.

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