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Detection of Tuberculosis Using Chest X-Rays

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***Abstract*— Tuberculosis (TB) is considered as a major health threat in many regions of the world. It is considered to be the world's second leading cause of death. So it is necessary to diagnose TB before it becomes fatal. But diagnosis of Tuberculosis is still a challenge and when left undiagnosed and thus untreated, it is seen that the mortality rates of patients with tuberculosis are considerably high. There are various diagnostic methods which are put into practice and those diagnostic methods are developed in the last century is still considered as the standard diagnostics. But these diagnostic methods are unreliable and slow. In order to reduce the burden of the disease, this paper proposes an efficient diagnosis of tuberculosis with the aid of chest radiographs. Lung region is the most affected part of Tuberculosis. At first, we extract the lung region from the chest radiographs using SIFT flow algorithm followed by graph cut lung segmentation method. After that for this segmented lung region, we extract various features, and from the features and using SVM classifier the x-rays are classified as TB affected or not. It also provides the information whether the patient is highly TB affected or TB starting level or no TB.**

***Index Terms*— Tuberculosis, SIFT Flow Algorithm, Graph Cut Algorithm, SVM classifier.**

I. INTRODUCTION

Tuberculosis is the short for Tubercle Basillus and is considered as a major threat in many regions of the world. Earlier, it was called as Phthisis, consumption or Phthisis pulmonalis. It is a widespread infectious disease and in many cases fatal, which is caused by various strains of mycobacteria, mainly Mycobacterium Tuberculosis. TB mainly affects the lungs of individuals but it can also affect other parts of the human body. It mainly spreads through air, mainly when people suffering from TB sneeze, cough or expel infectious bacteria when respiratory fluids are transmitted through the air. Infections which don't show symptoms are known as latent tuberculosis and about 25% of the people with TB are having latent TB.

TB is mostly seen in individuals in sub-Saharan Africa and Southeast Asia, and the main reason is poverty and malnutrition which reduces the resistance to the disease. There are various symptoms for detecting TB and it includes fever, chronic cough with blood tinged sputum, chest pain, night sweats, weight loss, fatigue, nail clubbing.

Treatment of Tuberculosis is difficult but several antibiotics exist for treating TB. The technique for diagnosing TB is the identification of Mycobacterium tuberculosis in a pus sample, which is considered as the current standard. But the disadvantage with this method is that, it may take several months to identify this slow-growing organism in the lab. Another technique is sputum smear microscopy. In addition, there are various skin tests are available for detecting TB but the skin tests are not always reliable. Molecular diagnostic tests are the latest development for detection of TB which are fast, accurate, and highly sensitive and are specific too. However, for these tests, additional financial support is required. Thus for computed aided diagnosis based detection of various lung diseases, accurate, sharp segmentation of lung boundary is necessary as discussed in [2] and [4].

In this paper, our work shows an automated approach for detecting TB in chest x-rays (CXRs) which are more accurate than the existing methods. A chest radiograph, which is colloquially called as a chest X-ray (CXR), or otherwise chest film. It is a projection radiograph of the chest which is used to diagnose conditions which affects the chest, its nearby structures and contents so that various diseases can be estimated. An automated technique of x-ray reading needs mass screening of large populations that could not be managed manually. For evaluating TB, a posteroanterior radiograph (x-ray) of a patient's chest is mandatory. Therefore we aim at a powerful TB diagnostics system, so a reliable screening system for TB detection using radiographs is needed. A CXR which is affected with TB will have cavitations, infiltrations, effusions, or military patterns in the x-ray images. Examples of normal CXR and abnormal CXR i.e., without and with TB infection are shown in fig.1 and fig.2 respectively.

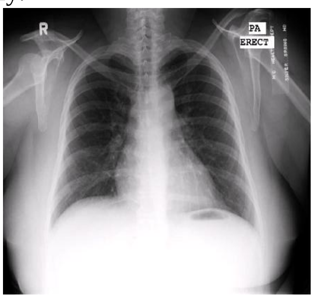

Fig. 1. Normal CXR

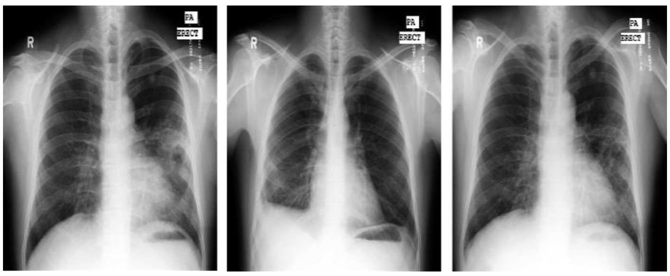

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Fig. 2. Abnormal CXR's. CXR A is having a cavitary infiltrate in the left side and a subtle infiltrate in the right lower lung. CXR B is having pleural TB. CXR C is having infiltrates in both left and right lungs.

II. SYSTEM OVERVIEW

This section presents the system overview and is shown in fig. 3. An automated approach for the detection of tuberculosis from CXR's is presented here and the steps include lung segmentation, followed by feature computation and classification of the input x-ray as TB positive or negative. At first, our system performs segmentation of the lung region of the input CXR using non rigid registration with a CXR database of pre-segmented lung regions in order to build a lung model as a guide combined with graph cut lung segmentation algorithm.

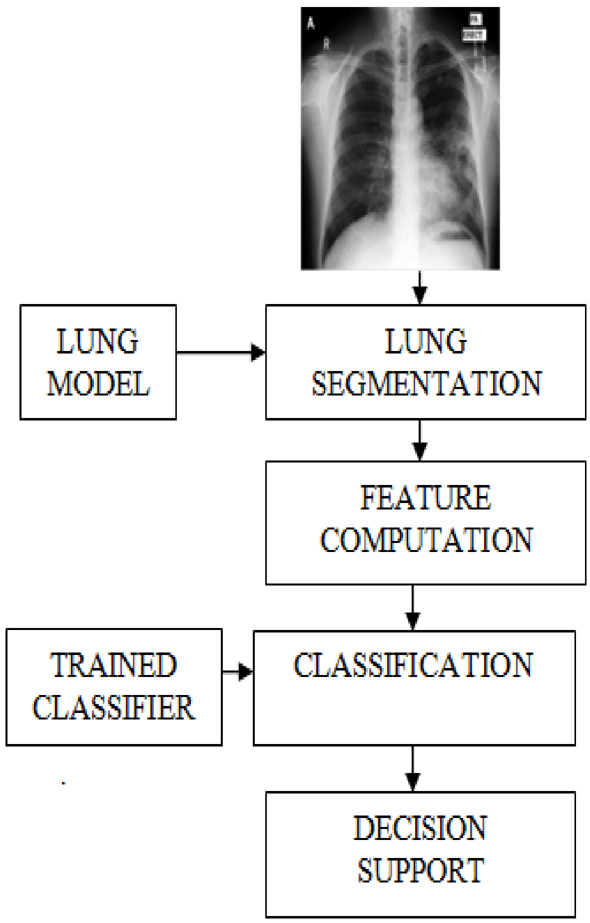

Fig. 3. System Overview

The graph cut methods are employed in [11].

Here we are incorporating a deformable lung model using a non-rigid registration algorithm based on SIFT flow. After that, for the segmented lung region, our system then computes a set of features and then the features are then fed as input to a pre-trained binary classifier. Finally, using decision support and thresholds, the classifier classifies the input CXR as a TB positive or not.

A. Lung segmentation- Patient-Specific Lung Atlas Model Using Non Rigid Registration

Here we propose a robust automated lung segmentation algorithm for segmenting lung region in chest X-ray images. Our method is shown in Fig.4 and it consists of three stages. At first we use a content-based image retrieval approach through which we identify a small set of lung CXR images which are most similar to the patient X-ray and it is done using partial Radon transforms which is combined with a Bhattacharyya similarity measure as proposed in [14]. The advantage of using partial Radon transform based retrieval method is its fastness. After ranking of the lung images, we then compute a lung model that is specific to each patient.

It is accomplished by warping the training database of CXR's to the patient X-ray using a deformable non registration algorithm. For estimating a patient specific lung model, we employ a deformable registration algorithm. First, it calculates the corresponding pixels between training CXR's and patient X-ray so that for each pixel it provides transformation mapping. Then using the transformation mapping, aligning of the training masks is performed. We then use the average of warped masks as a patient specific lung atlas. Finally, the lung boundaries are detected with a graph cut segmentation algorithm. Graph cuts algorithm models the segmentation process using an objective function in terms of boundary, region, and lung model properties. Here we show that our graph cut algorithm outperforms all other methods. Our proposed system combines two algorithms in a novel manner for lung segmentation in x-ray images.

B. Sift-Flow Algorithm

Here we use the SIFT descriptor which is considered as the best performing local feature descriptors. With the SIFT-flow algorithm, it models local gradient information of the observed x-ray image using the Scale Invariant Feature Transform (SIFT). The SIFT features of the chest X-rays are calculated in the following manner. First, at each pixel, the magnitudes and gradient orientations are computed. Then the computed gradients are weighted with a Gaussian pyramid in a n x n region which is done in order to enhance the influence of the gradient in the center region (e.g., n=16). After that, the regions are then subdivided into quadrants (e.g., n=4). Then in each quadrant, we form a gradient orientation histogram. It is formed by adding the gradient values to one of eight orientation histogram bins. This results in the concatenation of orientation histograms of the quadrants, which further results in SIFT descriptor vector for the center pixel of the nxn region. Once after calculating the SIFT features for the image pair, we the use the registration algorithm. It then computes pixel-to-pixel correspondences by matching the SIFT descriptors.

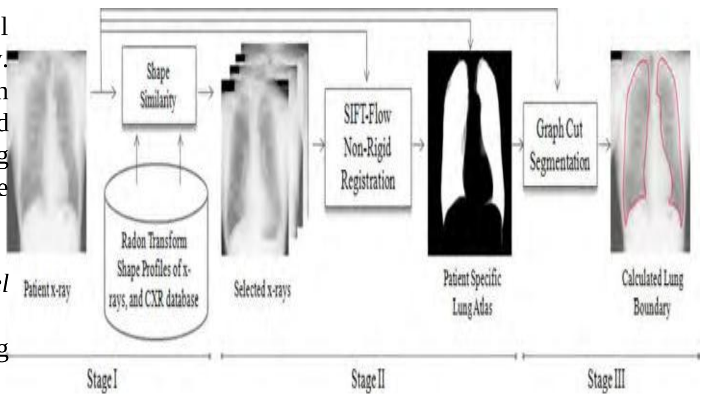

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Fig.4. Proposed Block diagram for Lung Segmentation

The registration stage of the proposed system is shown in fig.5.

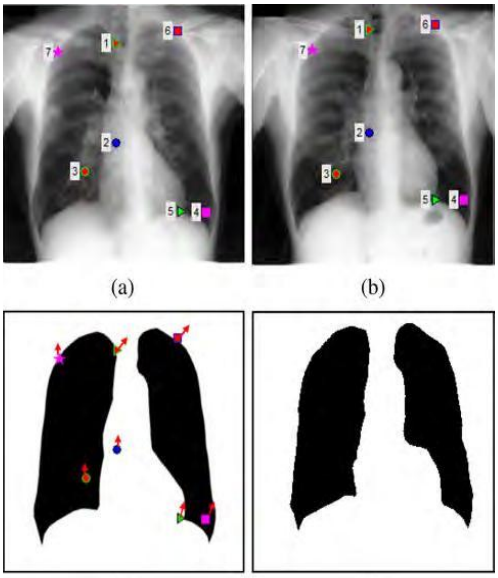
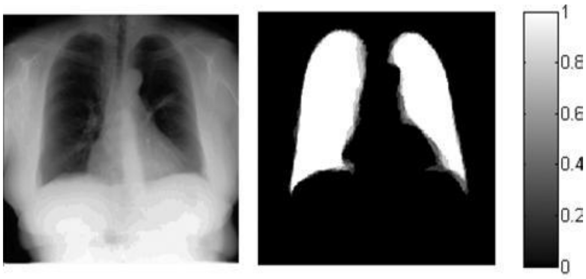


Fig. 5. Registration stage of the proposed system. The right one (b) is the X-ray of the patient, and the left one (a) is the x-ray which is most similar to the patient X-ray in the database. Colored markers denote the corresponding matches based on SIFT-flow features for sample pixels. (c) Transformation mapping is applied to all pixels , it is done by shifting the pixels in accordance with the spatial distances between the corresponding matches. (d) Warped lung model.

The patient specific lung model is determined from randomly selected CXR's and is illustrated in fig.6.



(a) (b)

Fig. 6. a). Randomly selected CXR's from database b) Patient specific lung model

C. Graph cut Algorithm

Our proposed system detects the lung boundary of the x-ray images with the help of lung model computed and from the image properties. Here, image segmentation is done using graph cut algorithm. This algorithm models computer vision problems by using an undirected graph G=(V,E). V is the set of vertices which represents the pixel properties such as intensity. E is the set of edges that connects these vertices. There are two extra vertices which represents the fg and the bg labels, and there are basically two types of edges, namely neighborhood edges and the edges which is between terminals and pixels. The graph structure is then formulated in an objective function which consists of a data term and a smoothness term. From the data term in the objective function, a solution which is consistent with the data, say image intensities is enabled. Smoothness term enables the algorithm to favor a smooth solution.. Edge weight is the spatial proximity measure between the vertices. To the data energy term, the edge weight between the terminals and pixels are integrated while the neighborhood edges are integrated into the smoothness energy term of the objective function. The objective function is formulated according to the desired criteria for segmentation. The criteria includes 1) the segmentation labels i.e., (fg/bg) should be consistent to the lung image intensities 2) the neighborhood image should be consistent to each other 3)the final segmentation should fit with the calculated shape model. The objective function is defined in terms of boundary, region and shape model properties of the pixels. Objective function is formulated as follows:

$$E(f) = \alpha 1 Ed(f) + \alpha 2 Es(f) + \alpha 3 Em(f) \qquad (1)$$

where Ed(f) represents the data term, Es(f) represents the smoothness term and Em(f) represents the lung model terms of the objective function. After formulating the objective function, we then compute the mincut which minimizes the objective function. The global minimum performs separation of the graph into two sub graphs i.e., graph which corresponds to some pixels that are connected to the fg terminal, and the other pixels are connected to the bg terminal.

D. Classification

Classifiers are used to detect abnormal CXRs with TB. For this we use a support vector machine (SVM), which classifies the computed feature vectors into either normal or abnormal i.e., whether the CXR is affected with Tb or not. Ideally, the feature vectors of abnormal CXRs will have a positive distance to the separating hyperplane, while the feature vectors of normal CXRs will have a negative distance. If the distance is larger, the more confident we are in the class label.

III. EXPERIMENTAL RESULTS

In this work, experimental results are obtained by applying the input CXR to our system. Lung segmentation is performed for the input CXR using non-rigid registration and SIFT flow algorithm followed by graph cut segmentation algorithm. The SIFT descriptors and the match points of the training CXR and the patient CXR is shown. This segmentation provides more accuracy than any other segmentation methods. The binary classifier finally classify whether the given input CXR of the patient is having TB or not. Presence of TB in patient is determined by detecting the presence of lung nodules in the CXR. There are various infiltrations, cavitations appear in the lung CXR image if the individual is affected with TB. Here, we perform lung segmentation, so that, the lung nodules can be determined from the CXR images. Manual detection of lung nodules is considerably inaccurate. Also lung segmentation methods with poor boundary segmentation do not achieve desired accuracy. Therefore, for a sharper segmented lung image, a more accurate decision can be made regarding the presence of TB or not.

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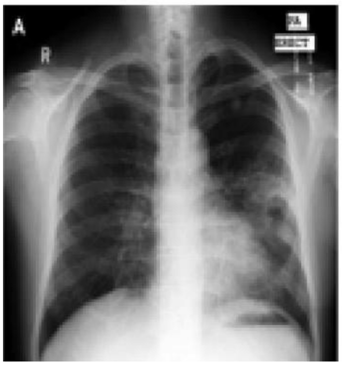

Fig. 4. Input image

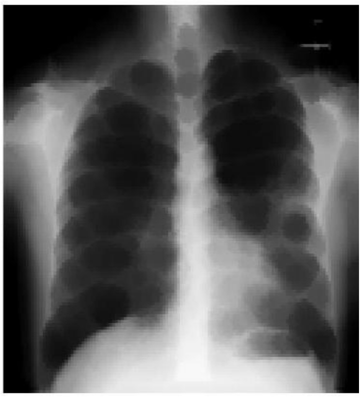

Fig. 5. Erode Image

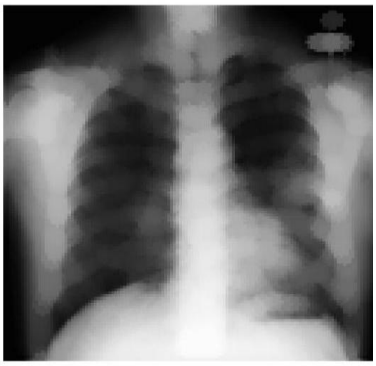

Fig. 6. Dilated Image

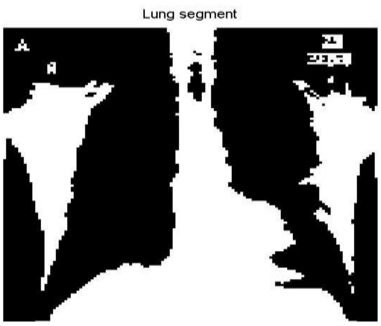

Fig. 7. Lung Segment

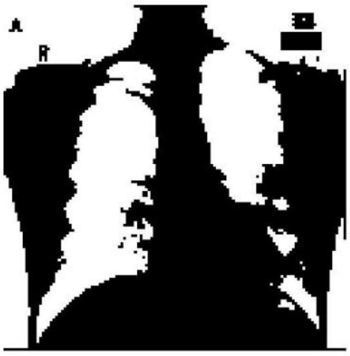

Fig. 8. Lung model

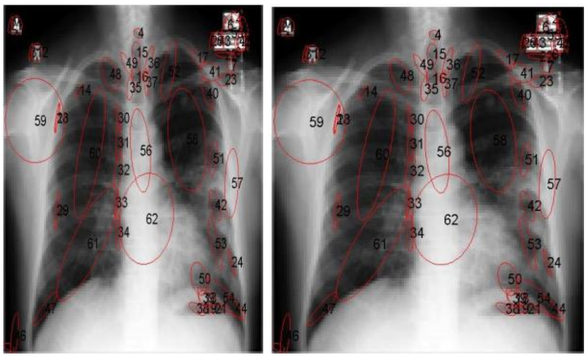

Fig. 9. SIFT Descriptor of the training CXR and the patient CXR

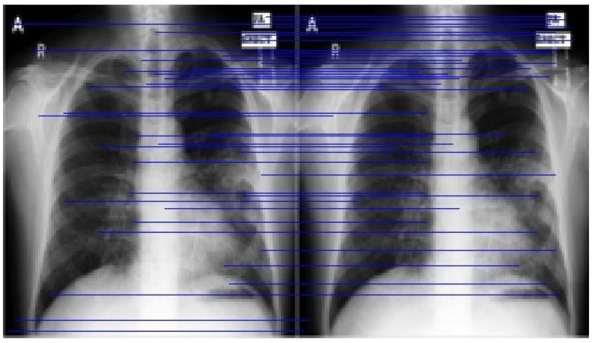

Fig. 10. Match points

Fig. 11. Segmentation results – red and red green contour indicate the automatic segmentation and gold standard results, respectively

IV. Conclusion

We have developed an automated system that screens CXRs for manifestations of TB in individuals. Here we present an efficient method of diagnosing TB from chest radiographs with the help of SIFT flow algorithm in combination with graph cut algorithm. The SIFT flow algorithm and graph cut algorithm provides an efficient lung boundary detection when compared with graph cut method alone. After that feature extraction is performed and finally we will classify the input CXR whether it is TB affected or not using SVM classifier. Here we proved that this lung segmentation method gives more accuracy in determining TB in CXR's. Further the future work is extended to compare our proposed work with the existing methods. Also the area of spread of TB will also be determined, so that we can determine how much percentage the percentage the person is prone to TB. Furthermore, for this method, various CXR database will be taken into consideration, and comparisons will also be manifested. Thus the experimental results indicate that the method shown here is a robust and effective method in TB detection. Therefore we proposed an automated system that screens CXRs for manifestations of TB with much accuracy of about 95%.

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