

Lung Segmentation for Tuberculosis by Using Active Appearance Model (AAM) In Chest Radiographs

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Abstract:

Tuberculosis is the extreme disease noted in the world. HIV/AIDS patients have an immune system which is impaired and that has made an impact on the problem. In the case of Tuberculosis the probability of mortality rate is not zero. In order to reduce the mortality rate the AAM (Active Appearance Model) in which training and segmentation process is undergone is used in the existing system. It is a method used for processing and analyzing manually traced segmentation examples during an automated training stage. Information about Image appearance and shape of lung structure is contained in a single model. But the major drawback is this method is not robust against occlusion. If the parts are occluded then they obtained result is unreliable. To overcome this problem we propose a Robust PCA (RPCA) method. By using this method computational effort is reduced and accurate reconstruction is also obtained. The results shows greater advantage for showing accuracy and speed for any distributed data.

Keywords: **Principal Component Analysis (PCA), Robust PCA (RPCA) , AAM(Active Appearance Model),Robust training and Reconstruction.**

I. Introduction:

TB is a major global health problem. There are many kinds of TB in which active TB includes multi drug treatment and it is an infectious disease caused by bacillus Mycobacterium tuberculosis and typical manifestation of TB is cavitation, miliary patterns, effusion and infiltration. These bacteria invade and multiply in different organs of the body. The symptoms are cough, phlegm, chest pain, weakness, weight loss, fever, chills and sweating at night. Infection like cavity formation in the upper lung zone is a strong indicator that TB has reached in to highly infectious state. Mass Chest screening can analyze cases of active TB to fight the epidemic. Even though the existence of a cheap cure,

tuberculosis (TB) is a leading killer of adults in the world. TB may concede itself in many radiographic patterns, but in most cases a chest radiograph of a TB patient contains areas with diffuse abnormalities. While mortality rates are high when left untreated, but the treatment with antibiotics enormously improves the chances of existence. In clinical trials, cure rates over 90% have been documented when we use these kinds of antibiotics. A poster anterior radiograph (X-ray) of a patient's chest is an essential part of every evaluation for TB. The chest radiograph includes all thoracic anatomy of the lung and it provides a immense output, given the low cost and single source.

In this paper we use Active Appearance Model (AAM). This model is known to be a computer vision algorithm which includes methods for acquiring, processing, analyzing, and understanding images for coordinating an analytical model of object shape and appearance to a new image. They are only built during a training phase. In many medical image segmentation challenges, the use of an above mentioned knowledge about the anatomical structure of interest is imperative in order to fetch a satisfactory result. This knowledge can be used to train an Active Appearance Model (AAM).

In this AAM model the best examples of this application in medical image processing are abundant for a wide range of different imaging modalities and anatomical structures. This paper mainly focuses on the training process and segmentation process of AAMs. Excellent results are executed and implemented underlining the possibilities of AAMs in daily clinical practice.

Bart M. ter Haar Romeny explains the continued interest in computer-aided diagnosis for chest radiography. The purpose of this survey is to categorize and briefly review the literature on computer analysis of chest images, The purpose of this survey is to categorize and briefly review the literature on computer analysis of chest radiographs with an emphasis on the techniques like FACD (fully automatic computer diagnosis), ICD (interactive computer diagnosis), and CAD (computer aided diagnosis)[2]. *Dieter Seghers* estimated A new generic model-based segmentation algorithm is presented, which can be trained from examples akin to the active shape model (ASM) approach in order to acquire knowledge about the shape to be segmented and about the gray-level appearance of the object in the image[7]. *Rui Shen* proposed an

automated segmentation technique, which takes a hybrid knowledge based Bayesian classification approach to detect TB cavities automatically. We apply gradient inverse coefficient of variation and circularity measures to classify detected features and confirm true TB cavities [8]. *Navneet Dalal* enumerates about the feature sets for robust visual object recognition, adopting linear SVM based human detection as a test case. After reviewing existing edge and gradient based descriptors, we show experimentally that grids of Histograms of Oriented Gradient (HOG) descriptors significantly outperform existing feature sets for human detection[10]. *Kannappan Palaniappan* demonstrated the performance of the approach within graph cut segmentation framework via qualitative results on chest x-rays. Experimental results indicate that predicted parameters produce better segmentation results. In this paper we claim that can be learned by local features which hold the regional characteristics of the image[11]. *Xinjian Chen* proposed a novel method based on a strategic combination of the active appearance model (AAM), live wire (LW), and graph cuts (GCs) for abdominal 3-D organ segmentation [13]. *S. Juhász* presented a solution for segmenting anatomical structures on chest radiographs. First we show an algorithm for the lung contour detection, and then we describe a method for finding the ribs and clavicles. [14]

However, the lung boundary detection algorithm which is used in this paper differs from the one used in our earlier publication. This method is proposed by using Robust PCA (RPCA) which is mainly uses the data reasoning and dimensionality reduction. To overcome the occlusion problem and to reconstruct the missing feature information is done by using Robust Reconstruction and Robust Training and the

outcome is obtained with greater accuracy and good speed.

II. Proposed technique:

Robust PCA:

Principal Component Analysis (RPCA) is a conversion of the widely used procedure which is statistical and works under grossly corrupted observed images. Principal Component Analysis (PCA) processes the Dimensionality Reduction technique for problems like classification.

It is also used for the purpose of representation of shape, appearance and motion in many given images. In typical PCA method the main drawback is that they are least square estimation technique and hence they decline to find out the outliers that are common in pragmatic training sets. mostly in Computer vision applications, outliers typically occur within the given image or sample due to pixels that are corrupted by occlusion, noise and alignment errors.

In order to remove this drawback we analyse the previous approach PCA to Robust PCA which uses an intra sample outlier process to find out outlier in the account of pixels. In this we use Quantitative comparisons with traditional PCA and robust algorithms illustrate about the benefits of RPCA in the presence of outliers.

If we take a normal training data it may possibly contain unwanted artifacts. It can be due to occlusion, noise, illumination or errors from data generation method like PCA.

If PCA space $U = [u_1, \dots, u_{n-1}]$ is estimates from n samples and an unknown sample $x = [x_1, \dots, x_m]$, $m > n$ can consistently be reconstructed to a known degree of accuracy by $p, p < n$, eigen vectors. where \tilde{x} is the

sample mean and $a = [a_1, \dots, a_k]$ are the linear coefficients. but if the sample x contains outliers then it would not yield a decisive reconstruction, so far a robust method is required thus in the following method we propose a more competent Robust PCA approach.

$$x = u_p a + x = a_j u_j + x$$

Robust Training:

The training procedure is the initial stage in this RPCA and this is mainly subdivided in to two major parts. First a standard PCA subspace U is generated using fill available training data. Second step is that the N sub samplings S_n are established from randomly selected values from each data point. For each sub sampling S_n a smaller sub space U_n is estimated in addition to the full subspace.

Robust Reconstruction:

In this second stage an new unseen test sample x is given then the robust \tilde{x} estimated in two stages. in the first stage the outliers are detected based on the reconstruction errors of sub-subspace. in the second stage using the estimated inliers a robust reconstruction x of the whole sample is generated.

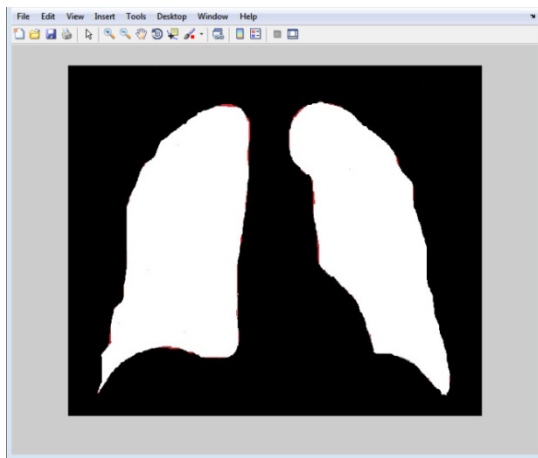
Lung input image:



In the gross outlier detection initially N sub-sampling S_n are generated according to the corresponding sub-spaces U_n and in addition we also define the set of inliers r as the union of all selected pixels $r = S_1 \cup \dots \cup S_N$ and this allows to estimate the error maps

$$e_n = |s_n - \tilde{s}_{ns}|$$

Lung atlases:

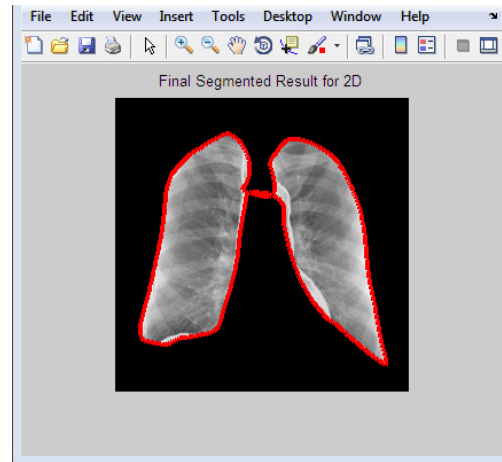


Now the mean reconstruction error \bar{e} over all sub-samplings and mean reconstruction error \bar{e}_n for each of the sub samplings. by taking all these errors we are able to detect outliers by local and global thresholding. the local threshold are defined by

$$\theta_n = e_n \omega_n$$

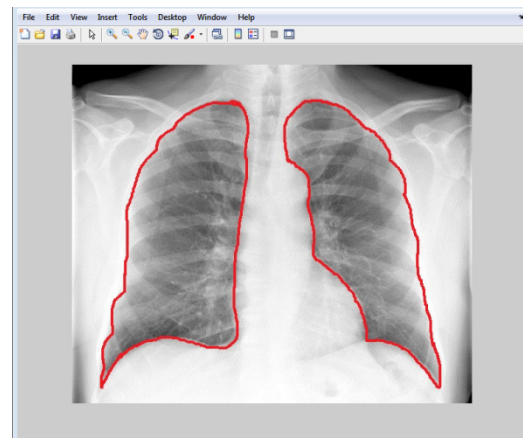
Where ω_n is weighing paprameter and globsl threshold θ is to be set the mean error \bar{e} .

Final segmented result of 2D:



Finally the set of inliers are redefined by $r = S_1 \cup \dots \cup S_q$. hence in the gross outlier detection procedure it allows to discard the outliers so the obtained set contains only the inliers. in general the robust estimation of the coefficients is computationally very capable of removing outliers. in this only simple matrix operation is performed that is very quick and agile. the part which is very expensive is refinement step in which linear system of equation is repeatedly solved and due to this the runtime is kept low.

Lung boundary detection:



III Result analysis:

To show the benefits and advantages of proposed robust PCA method (RPCA), we compare it to the standard PCA and the Robust PCA approach. We choose the latter one, since it yields superior results among the presented methods in the literature and also the refinement process it's similar to theirs as well.

IV Conclusion:

We have developed a novel robust PCA (RPCA) method based on its ability and efficiency as there is two-stage outlier detection procedure. Our main idea is to estimate a large number of small PCA sub spaces from a subset of points. From those sub spaces and the given test samples largest errors are discarded that will reduce the number of outliers in the input data called as gross outlier detection. The gross outlier detection is computationally cheaper when compared to refinement and the proposed method decreases the putting effort for the robust reconstruction. In our experiments our new robust PCA shows existing methods in terms of speed and accuracy and it is also applicable in practice for real-time applications such as Robust Active Appearance Model (AAM) fitting

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