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Detection of Cardiomegaly using Lung Boundary Segmentation

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ABSTRACT: To decrease the mortality and to save the lives of patients suffering from pulmonary disease a National Library of Medicine (NLM) is developing a digital chest x-ray (CXR) screening system for deployment in resource constrained communities. An important step taken in the analysis of digital CXRs is the automatic detection of the lung regions in chest X-ray. In this paper, we present a graph cut based robust lung segmentation method which will detects the lungs with high accuracy. This method consists different stages such as (i) average lung shape model calculation, and (ii) lung boundary detection based on graph cut. Preliminary results on public chest x-rays demonstrate the robustness of the method. The National Library of Medicine (NLM) is now developing digital chest X-ray (CXR) detection &screening system for deployment in resource constrained communities and developing countries worldwide and with a focus on early detection of pulmonary diseases. A critical component in the computer-aided diagnosis of digital CXRs is the automatic detection of the lung regions. In this paper, we present a nonrigid registration-driven robust lung segmentation method using which an 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: 1) a content-based image retrieval approach (CBIR) using a partial Radon transform and Bhattacharyya shape similarity measure,2) creating the initial patient-specific anatomical model of lung shape using SIFT-flow for deformable registration of training masks to the patient CXR and 3) Extracting refined lung boundaries using a graph cuts optimization method 4) SVM Classifier.

KEYWORDS:CAD, radiographs, segmentation, SVM Classifier, SIFT, Graph cut

I. INTRODUCTION

Important step of computer-aided diagnosis is to detect the lung regions in chest x-ray images. Researchers are developing a computer-aided system for various pulmonary diseases like screening using chest x-ray radiographs. One of the important first steps of the system is to detect the lung regions accurately in chest radiographs. In this paper, we present a graph cut based robust lung detection system designed for this project. Then using SVM classifier we will find out the disease called as cardiomegaly. Processing of x-ray chest images poses some challenges. For example, for lung segmentation, the strong edges at the rib cage and clavicle region cause local minima [1] for most minimization approaches. Segmenting the lung apex is also a nontrivial problem because of the changing intensity at the clavicle bone. Additionally there are certain challenges such as segmenting the small costophrenic angle, making allowances for anatomical shape variations such as varying heart dimensions or other pathology, and the x-ray imaging inhomogeneity's[2].

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II. RELATED SURVEY

In Over the past decade, a number of research groups have worked on chest X-ray analysis, and various methods have been proposed for lung boundary segmentation. We survey some of the recent results in X-ray image based lung segmentation. 1) Bidirectional chain coding method 2)Pixel Classification based segmentation 3)Deformable Models based 4)Fuzzy segmentation method 5)Hybrid method 6) Rule based segmentation method7) Watershed Transformation 8)Divide and Conquer Homogeneity algorithm 9) Novel Approach

A variety of image processing and analysis methodologies has been proposed for the segmentation of plain chest radiographs. Many of them have focused on the segmentation of the lungdistance between the nodes, number of hops and transmission time are also considered for optimization. Whereas fewer have focused on the segmentation of the rib cage or other anatomic structures of the chest.

The first type relies on Bidirectional chain coding method [3]which offers their designer the freedom to express his knowledge about the problem in any type or processing imaginable. A bidirectional chain coding method combined with a support vector machine (SVM) classifier [6] is used to selectively smooth the lung border while minimizing the over segmentation of adjacent regions. This automated method wastestedon233computedtomography (CT) studies from the lung imaging database consortium representing juxta pleural nodules.

Another approach for lung segmentation method is Marker based watershed transformation [4]This method implements marker based watershed transformation [4] with the combination of both watershed transformations. In segmentation could be used for occlusion boundary, object recognition estimation within stereo or motion systems, image compression, image database look-up or image editing. Existing system segmentation is limited, But this System perform the segmentation for the lung image.

Computer Aided Diagnosis (CAD) [1] system allows detection of lung cancer through analysis of chest CT images. Two problems have been focused; one is segmentation of organ of interest, which in case of Lungs is already a challenge. Second is classification, in which nodule features (like geometric properties, image intensity, shape and size) have to be taken into consideration. The objective of this study is identify all nodules from the chest CT lung images and classifying these nodules into cancerous (Malignant) [5] and non-cancerous (Benign) [7] nodules, to reduce the false positive rate using Image processing techniques and Neural Network techniques

In fuzzy segmentation method [8] the detection of the lung field boundaries is done. Once the boundaries of the lung fields are identified, physiological measurements of the lung features are possible. The properties of the boundary are determined by edge detection along with suitable filter algorithms. The aim of proposed work is to develop an experimental system which is segmented and analysis of the lung boundaries [7] in chest X-ray images. These results obtained quite satisfactory. This is tried to make a sharp distinction between the lung region and the exterior of the lung.

In Rule based method,[9] neural networks are ideal in recognizing diseases using scans and since there is no need to provide a specific algorithm on how to identify the disease. This paper describes an algorithm to separate the lung tissue [10] from a Chest CT to reduce the amount of data that needs to be analyzed. So, in this aim is to have a fully automatic algorithm for segmenting the lung tissue, and to separate the two lung sides as well.

In Digital Image Processing, neural networks are ideal in recognizing diseases using scans since there is no need to provide a specific algorithm on how to identify the disease. This paper describes an algorithm to separate the lung tissue from a Chest CT to reduce the amount of data that needs to be analyzed. Finally, a sequence of morphological operations is used to smooth the irregular boundary.

Lung Computer-Aided Diagnosis (CAD) [2] is a potential method to accomplish a range of quantitative tasks such as early cancer and disease detection, In computer-aided diagnosis of lung disease, accurate and fast pulmonary parenchyma segmentation is the core step. Watershed algorithm [4] is used in this paper to segment and extract lung parenchyma. To reduce over-segmentation, an improved watershed segmentation method which marks foreground and background is proposed. this proposed one requires less computational complexity, more simple parameters, and can effectively reduce over segmentation

Another approach where integration of spatial relations [8] in the process of segmentation of chest radiography. In the proposed approach, spatial relations are represented as fRule based segmentation method uzzy subsets of the image space. Using this strategy, we imitate the reasoning of a physician when interpreting a medical image. The results demonstrate that the introduction of spatial relations can improve the recognition and segmentation

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of structures with low contrast and ill-defined boundaries. Image segmentation is an important step in many computer vision algorithms.

III. WORKING

Segmentation poses a number of challenges in medical imagingincluding noise [12] motion during imaging, sampling artefacts caused by the acquisition equipment, low contrast, deformation of tissues,shape variations due to normal anatomy and disease. So,here first we use a content-based image retrieval approach [13] to identify a small set of lung CXR images that are most similar to the input patient X-ray image using partial Radon transforms and Bhattacharyya similarity measure.The partial Radon transform based retrieval method is fast and can accommodate small affine distortions in the CXR. Then using SIFT we will find out key points called [14]as pixels which are present on boundary line of lungs. Thenfinally, the lung boundaries are determined using a graph cuts discrete optimization approach with a customized energy function. This includes a novel anatomical atlas shape prior term which ensures close adherence to normal lung anatomy.After finding out the lung boundary the image is given to SVM classifier which uses an Euclidian distance as a measure to find whether input patient image is normal or cardiomegaly. Following is a block schematic for the proposed system in which a lung boundary is identified and then it is given to classifier to identify the disease.

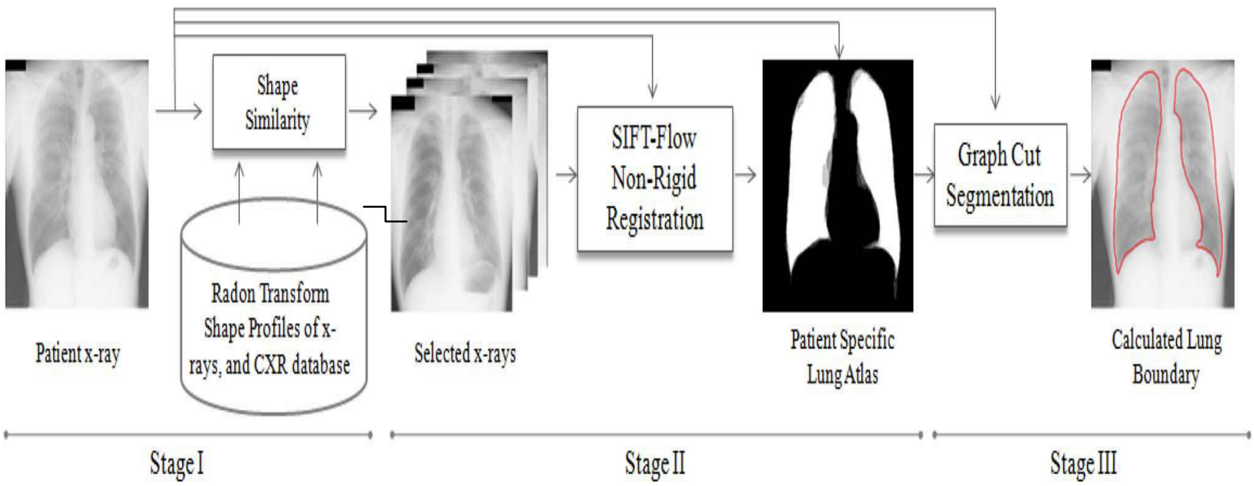

Fig1.Bloch schematic for lung boundary detection

A.CBIR

In content based image retrieval approach we first identify a small subset of images (i.e. three) in the training database which are most similar to the patient query image, using a content-based image retrieval (CBIR) [12] approach we use this subset of training images to build an accurate lung model while significantly speeding up the step of nonrigid registration between the training and the patient query images. Also we use partialRadon transforms, or orthogonal projection profiles, to compare and rank the similarity between two patient's lung images. The Radon transform projection along an arbitrary line in the plane is defined as

$$R(\rho,\theta)=\int\int I(x,y)\ \delta(\rho-x\cos\theta-y\sin\theta)dx\,dy............(1)$$

Where,δ is an implicit function and $x\cos\theta$ and $y\sin\theta$ are horizontal and vertical projections. The horizontal and vertical projection profiles are precomputed for all images in the training database to speed up the CBIR search process

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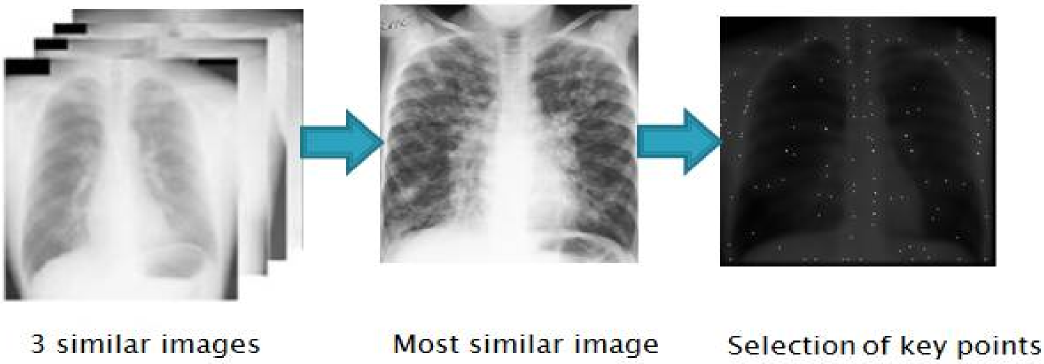

Fig.2 CBIR approach for matching of images

Here, we first calculate the intensity projection of the images in the vertical and the horizontal directions. Here we use a small subset of angles which we refer to as the partial Radon transform and use these few projections for image matching and similarity assessment. The partial Radon transform projection [10] method is fast to compute compare and rank thesimilarity between two patient's [14] lung images. It ranks the similarity between two images and compare two images.It has various advantages such as it is easy to interpret & fast to compute. Then we measure the similarity of each projection profile between the atlas database and the patient chest X-ray using the average Bhattacharyya coefficient which is given by,

$$\mathbf{BC(I1,I2)=\alpha\ \Sigma\sqrt{p1(x)p2(x)}+(1-\ \alpha)\ \Sigma\sqrt{q1(y)q2(y)}\ldots\ldots..(2)}$$

Where, p1(x) and p2(x) are the horizontal projections, andq1(y)and q2(y) are the vertical projections of images and I1,I2 are the two images to be compared respectively x and y are the histogram bins of the projection profiles, and n and m are the number of bins in the profile histograms and $\alpha = n/(n+m)$ is the relative weight for each profile.

B.SIFT-Flow Deformable Warping of Lung Atlas

There are various image processing operations such as Image registration [17] which is an important task for many medical applications such as comparing/fusing images from different modalities, tracking temporal changes in medical images collected at different times. A registration scheme [11]calculates a transformation mapping from source image to target image by matching corresponding pixels of images. Correspondences can be calculated by either for each pixel or only for salient locations such as edge points or corners. These images can be modelled using local feature descriptors such as Scale Invariant Feature Transform (SIFT),[21] or using a combination of gradient, shape, and curvature descriptors. In this work, we use the SIFT descriptor which is among the best performing local feature descriptors are best performing local discriptors.The correspondence matching is formulated using the following objective function:

$$\begin{gathered}\mathbf{E(w)=\ \Sigma\ \min(\|s1(p)-s2(p+w(p))\|,t)+}\\ \mathbf{\Sigma\ (|u(p)|+|v(p)|)+}\\ \mathbf{\Sigma\ \min\ (|u(p)-u(q)|,d)+}\\ \mathbf{\min(|v(p)-v(q)|,d)\ldots\ldots\ldots\ldots\ldots(3)}\end{gathered}$$

Where, p is the set of pixels in the X-ray, N is the spatial neighbourhood set, and s1 and s2 are the SIFT images in which each pixel is represented by a SIFT descriptor vectorw(p)=(u(v),v(p)) are the flow vectors at p and are t and d are the truncated thresholds. A minimization algorithm calculates the SIFT-flow by minimizing the objective function. The first term of the objective function forces the algorithm to match pixels according to their SIFT descriptors, [20] with warping based on the registration flow vector w(p). The second term constrains the flow vectors to be as small as possible. The third term constrains the flow vectors of number of pixels to be similar.

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C.Graph cut:

The system detects the lung boundary of X-ray images using various image properties [12] and the lung model calculated in the previous stage. We perform image segmentation using graph cuts and model the segmentation process with the objective function. The max-flow min-cut algorithm minimizes the objective function to find a global minimum which corresponds to the foreground (fg) and the background (bg) labelling of the pixels. This section provides the details of the segmentation component of our system. The graph cuts algorithm models computer vision problems using an undirected graph.The set of vertices represents the pixel properties such as intensity.

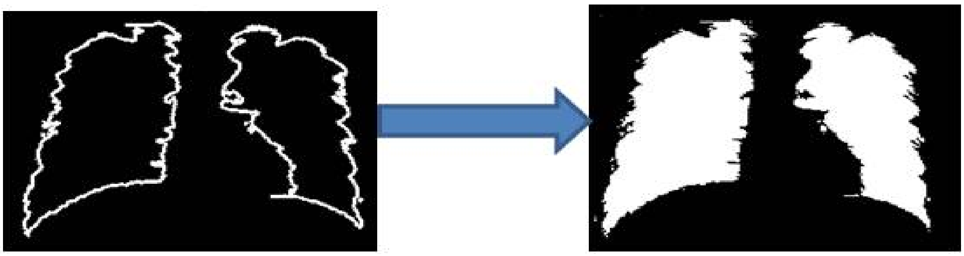

Fig3.Formation of lung atlas

D.Objective Function

The objective function is formulated based on the desired segmentation criteria which includes 1) the segmentation labels (fg/bg)should be consistent with the image intensities of the lung; 2) the neighborhood labels should be consistent with each other, and lastly 3) the resulting segmentation should fit the calculated shape model. Let,f=(f1…fp….fP) be a binary vector whose components correspond to fg/bg label assignments to pixels, where f is the set of pixels of the image. The algorithm aims to find an optimal configuration of according to the specified constraints. Based on the segmentation criteria, we define the objective function in terms of boundary, region, and shape model properties of the pixels as follows:

$$E(f)= \alpha 1Ed\,(f)+ \alpha 2Em(f)+ \alpha 3Es(f)\ldots\ldots\ldots\ldots..(4)$$

We incorporated here the patient specific lung atlas model into the graph edge weights between the terminal nodes and pixel nodes [13].As explained above the lung model is calculated by registering the top most similar X-rays to the patient X-ray. It is formed as a 2-D array [25] that has same size as the observed image and contains the probabilities of the pixels being part of the lung field..

E.SVM Classifier: SVM is Support vector machine classifier or support vector network classifier [15].It is used to analyze data and recognize pattern It gives representation of different pixels present in particular space. SVM gives representation [11] of points in space and performs nonlinear classificationSVM is Support vector machine classifier or support vector network classifier It support vector machines which is used for classification and regression analysis. Euclidian distance which is It is a metric used to measure distance between two points also measures the straight line distance between two pixels. It is given by to classify the normal and cardiomegaly images using the formula

$$d(p,q)=d(q,p)=\sqrt{\Sigma(qi-pi)^2}\ldots\ldots\ldots..(5)$$

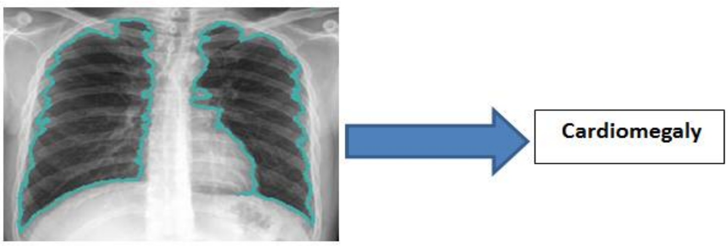

Fig4.Detection of cardiomegaly

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IV. EXPERIMENTAL RESULTS

In this work, we evaluated the proposed lung segmentation algorithm using three parameters. The only publicly available database for evaluating lung segmentation in chest X-ray imagery is the Indian dataset. In this work, we evaluated the proposed lung segmentation algorithm using three different CXR datasets.

A. Evaluation Metrics

Literature proposed several algorithms with different evaluation metrics. In order to compare our segmentation quality with the segmentation performances in the literature, we used three commonly used metrics.

1.TheJaccard Similarity Coefficient (overlap measure) It is the agreement between the ground truth (GT) and the estimated segmentation mask (S) over all pixels in the image. We formulate it as follows:

$$\Omega=|S\cap GT|/|S\cup GT|=|TP|/|FP|+|TP|+|FN|\ldots\ldots\ldots\ldots(6)$$

where TP (true positives) represents correctly classified pixels, FP (false positives) represents pixels that are classified as object but that are in fact background, and FN (false negatives) represents pixels that are classified as background but that are in fact part of the object .When five random cardiomegaly and five Normal images are considered then the graph of obtained after calculation is as follows:

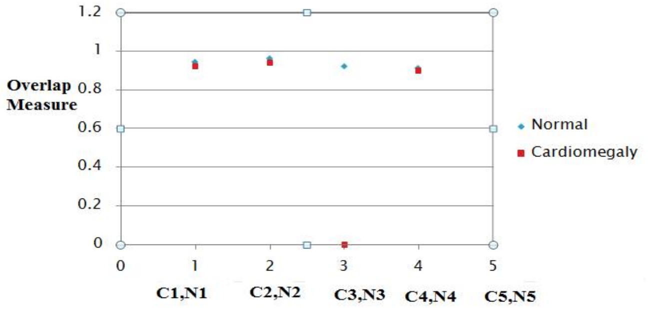

Fig.5.Graph of Overlap measure

*2.Euclidian distance:*It is a metric used to measure distance between two points Measures the straight line distance between two pixels It is given by,

$$d(p,q)=d(q,p)=\sqrt{\Sigma(qi-pi)^2}\ \ldots\ldots\ldots\ldots(7)$$

wherei is equal to 1 to n

When 10 normal images are taken from database and 10 cardiomegaly images taken froma database it is found that the whwn 0.1<d >0.49 then the patient is normal and has no dieaesase whereas when 0.5<d>1 then the patient is affected with cardiomegaly. When ten cardiomegaly images and ten normal images are observe under this parameter graph for Euclidian distance as measure isgiven below:

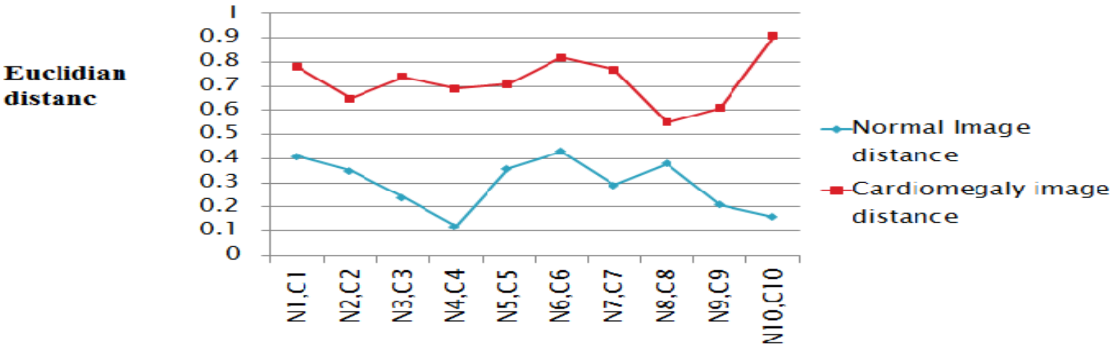

Fig6.Graph of Euclidian distance for cardiomegayvs.Normal image

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*3.Time requirement:*After experimental it found that when stopwatch is set for normal patient x-ray the total time requirement is in between 82 to 86 seconds whereas for Cardiomegalised disease the time is always more than 86 seconds as it indicates the maximum time require to detect the diseases.

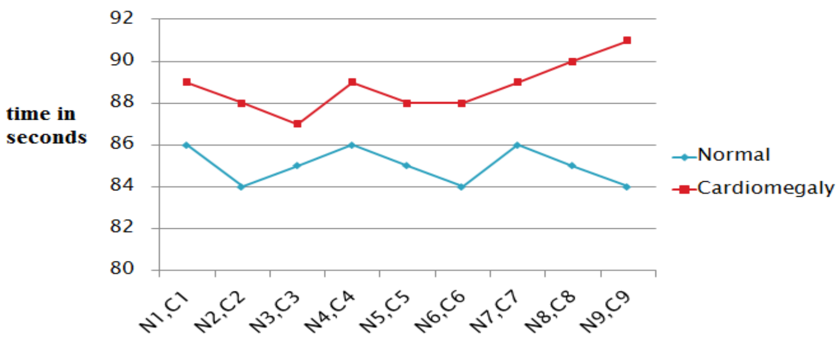

Fig7.Graph of time required for cardiomegaly vs. Normal image

The lung segmentation algorithm is only one component of a full CAD pipeline for tuberculosis screening using CXRs. A fielded system working in rugged conditions with minimal access to technical and healthcare experts needs to be robust in terms of accuracy and near realtime in terms of performance. Image subsampling to a lower resolution prior to segmentation speeds up runtime significantly while having a negligible impact on accuracy. The computationally expensive numerical algorithms for energy optimization are implemented in C++ and other parts in Matlab.We report the execution times of our lung segmentation algorithm on a desktop personal computer with a 2.53-GHz Intel Xeon CPU and 4 GB of memory in Table III.

V.OUTPUT

Output on MATLAB R2013afor the proposed method is as shown in the figure below:

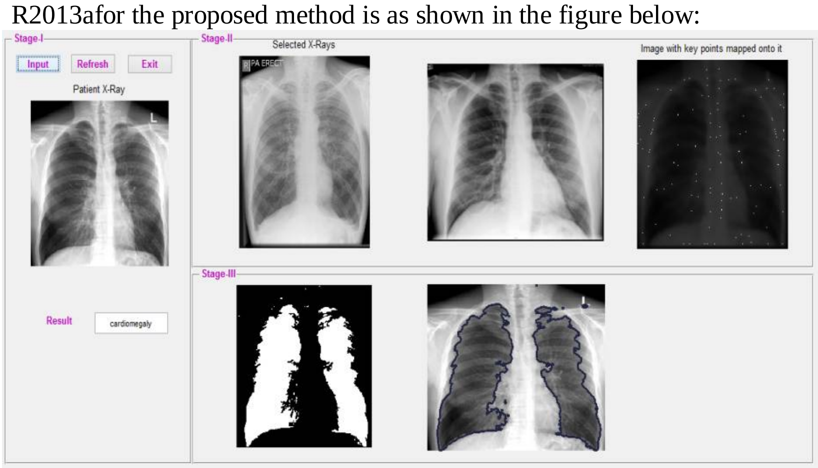

Fig8.Detection of cardiomegaly using Lung segmentation

V.CONCLUSION

We develop a computer aided system for screening and detection of Cardiomegaly disease using patient's chest radiographs in which we have found out a disease called cardiomegaly using boundary detection technique called lung boundary segmentation which includes different methods like Partial radon transform for similarity selection, Bhattacharya coefficient, SIFT i.e. Scale invariant feature transform for nonrigid registration, Graph cut method to refine the graph obtained at end, SVM classifier for classification of normal and cardiomegaly image etc.Thus, most

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advantageous in analysing such diseases which are based on lung boundary is a user friendly approach ,low cost application and can be easily implement. It can give the near to accurate result in boundary detection. The only limitation to the method is radio opaque objects which will not give the better CXR of patient. Thus,the results will indicate the robustness and effectiveness of the proposed approach when applied to CXRs collected in different geographical regions.

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