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A Review on Segmentation of Chest Radiographs

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Abstract - *Medical image processing is a fast and active growing field. There are different modalities(X-ray, CT, MRI, Endoscopy and many more) used to create medical images. Chest Radiograph is an image of the chest used to diagnose conditions affecting the chest. The segmentation of medical image is required to simplify the representation of an image into something meaningful and easier to analyze. Segmentation of anatomical structures from medical images is used for diagnosis, monitoring and treatment analysis. There are many medical image segmentation techniques. This paper compares the salient features of the segmentation techniques like Active Shape Models(ASM), Active Appearance Model(AAM), Multiresolution Pixel Classification(PC), Visual Saliency based method, Deep Convolutional Neural Network, etc.*

Key Words: Computer-aided diagnosis(CAD), Chest X-ray(CXR), Segmentation, Principle Component Analysis(PCA), Active Shape Model(ASM), Active Appearance Model(AAM), Pixel Classification(PC).

1.INTRODUCTION

In image processing, segmentation is the process of partitioning an image into different segments such as pixels. Image segmentation is typically used to locate the objects and their boundaries. There are several practical applications of segmentation, some of them are Content-based image retrieval, Machine vision, Object detection, Recognition tasks, Traffic control systems, Video object co-segmentation, and action localization, etc.

The segmentation of biomedical images deals with the partitioning of an image into multiple regions representing anatomical objects of interest. In more precisely Image segmentation is the process of assigning a label into every pixel in an image. The pixels with the same label share certain features. The result of image segmentation is a set of segments that covers the entire image. The different pixels in a region are similar with respect to certain characteristics such as color, intensity or texture.

X-ray is one of the modalities used for creating medical images. Chest Radiography is used to generate images of the chest. Chest X-ray(CXR) is used to diagnose conditions affecting the chest and its nearby structures. Conditions that can commonly be identified from chest radiography are Pneumonia, Pneumothorax, Interstitial lung disease, Heart failure, Bone fracture, and Hiatal hernia. Segmentation of anatomical structures from chest radiographs is the most popular research topic. The next section deals with the different segmentation methods used for segmenting the chest radiograph.

2. SEGMENTATION METHODS

The prerequisite step for developing a computer-aided diagnosis(CAD) system is Segmentation. The intensity of pixels, texture associated with each pixel, etc, can be used for segmentation. There are numerous algorithms have been developed for segmentation. The fundamental concepts and techniques behind each algorithm are different. This section compares different algorithms developed for segmentation based on accuracy, specificity, and sensitivity.

S. G Armato et.al[1] developed and tested an automatic lung segmentation in digitized posteroanterior chest radiographs. It is a gray level thresholding based approach. Initially, Gray level histogram analysis was performed to find the range of thresholds. Then the thresholds are used in the iterative Global Gray level thresholding approach. Then the local gray-level thresholding was performed on the output of global thresholding. The resulting contours were undergone several smoothing processes including a rolling ball technique. The final contours give a close approximation of the boundaries of the lung regions. This method provides 79% of accuracy.

B V Ginneken et.al[2] provides segmentation of anatomical structures in chest radiographs using the supervised method. They provide a comparative study on the public database. The different methods used for segmentation was Active shape models(ASM),Active appearance model(AAM),Multiresolution pixel classification(PC).ASM is the most popular method and it has several internal parameters. Gray level appearance model and multi-resolution ASM are essential to obtain good segmentation results. The input to the AAM was similar to that of the input to the ASM.ASM considers the combined model of shape and appearance but AAM considered all object pixels. Pixel classification(PC) gives the best results compared to ASM and AAM.

Y Shi et.al[3] proposed a deformable model using population-based and patient-specific shape statistics for the segmentation of lung fields from chest radiographs. The proposed method uses the scale-invariant feature transform for the characterization of image features. The proposed method is more robust and accurate compared to other active shape models in segmenting the lung fields from the chest radiographs.

D K Iakovidis et.al[4] proposed a segmentation method based on Bezier Interpolation of salient control points. The methodology involves the detection of salient points on the anatomical structures around the lung regions by edge feature extraction techniques. Then the detected salient points are interpolated by Bezier curves. This method doesn't exclude the overlapping regions of the heart from the lung fields. This method also possesses other abnormalities. The abnormalities originating from bacterial pulmonary infections don't affect the segmentation procedure. This method produces accurate segmentation of portable radiographs.

Z Shi et.al[5] proposed a Gaussian kernel-based FCM with spatial constraints for the segmentation of chest radiographs. The objective function in the conventional fuzzy c-means algorithm using a Gaussian kernel induced distance metric. The spatial penalty term is formed by considering the influence of the neighboring pixels on the center pixel in chest radiographs. This method is efficient and effective. The accuracy of this method is about 96%.

P Annangi et.al[6] proposed a region-based active contour method for lung segmentation in chest radiographs using prior shape and low-level features. The local minima due to shading effects and the presence of strong edges due to the rib cage and clavicle are the challenges while using the active contours for lung segmentation.

T Xu et.al[7] developed an edge region force guided active shape approach for automatic lung field segmentation in chest radiographs. The proposed technique is to address the inadequacy of the active shape model in lung field segmentation from chest radiographs. This method achieves 3-6% improvements on accuracy, sensitivity, and specificity compared to traditional active shape model techniques.ASM has mainly 3 stages, they are shape learning, segmentation, and initialization. This method also uses PCA analysis to learn about the lung fields.

L Hogeweg et.al[8] proposed an automatic technique to segment the clavicles from posterior-anterior chest radiographs. Where three methods are combined together, they are pixel classification, ASM segmentation and finally dynamic programming. Pixel classification is applied separately for the interior, the border and the head of the clavicle. The output of pixel classification is given as input to the ASM segmentation. Finally, dynamic programming is performed. Which is performed with an optimized cost function that combines the appearance information of the interior of the clavicle, the head, the border and shape information obtained from the ASM segmentation.

S Candemir et.al[9] proposed a nonrigid registration driven robust lung field segmentation from chest radiographs. This method uses image retrieval based patient-specific adaptive lung models, that detects the lung boundaries. This method has three main stages. Initially, there is a content-based image retrieval approach, which is to identify the training images similar to the patient chest radiographs by using partial random transform and Bhattacharya shape similarity measure. Secondly created the initial patient-specific anatomical model of lung shape using SIFT flow, which is for the deformable registration of training masks to the patient chest radiographs. Finally extracts the refined lung boundaries using a graph cuts optimization approach with a customized energy function. The proposed method provides an accuracy of 95.4% on the JSRT database.

X Zhang et.al[10] proposed a marker-based watershed method for the chest radiograph segmentation. This method is used to segment the background of chest radiographs. This method consists of six modules. They are image preprocessing, gradient computation, marker extraction, watershed segmentation from markers, region merging and background extraction. The dice coefficient obtained from the proposed method is better than that of the manual thresholding and multiscale gradient-based watershed method.

T A Ngo et.al[11] proposed a hybrid method based on a combination of distance regularized level set and deep structured inference for the lung segmentation in chest radiographs. This method combines the advantages of deep learning methods and level set methods. The deep learning method provides robust training with few annotated samples and top-down segmentation with structured inference and learning, and level set methods use to shape and appearance priors and efficient optimization techniques. The proposed method provides accuracy about 94.8%-98.5% on the JSRT database. The running time for the proposed method is in between 20-25 seconds per image.

P Pattrapisetwong et.al[12] proposed a lung segmentation method based on shadow filter and local thresholding. This is an unsupervised learning method for lung segmentation. This method consists of three processes, they are, preprocessing, initial lung field estimation, noise elimination. At the initial step, the original images are resized and contrast enhancement was performed. The lung outlines are enhanced by a shadow filter. At the second step, initial lung field estimations are obtained by local thresholding then detect outer body regions and filtered the regions based on their property. Finally, the noises are eliminated by morphological operation techniques. The accuracy of this method is around 96.95% on the JSRT database.

P Chondro et.al[13] proposed a low order adaptive region growing for the lung segmentation on plain chest radiographs. This method incorporates an avant-garde contrast enhancement there by the opacity of the lung regions are increased. Initially, the region of interest is localized by implementing a brisk block-based binarization and morphological operations. By the use of a statistical-based region growing with an adaptive graph cut technique for the improvements on region boundaries, the accuracy is increased. Then the accuracy is around 96.3%.

X Li et.al[14] proposed a visual saliency-based method for the automatic lung region extraction from chest radiographs. This method is based on the observation that the lung fields in the chest radiographs will stand out against the background. Initially, the chest radiograph image is segmented into small subregions by graph-based segmentation. Then found the salient value of each sub-regions by global contrast function. The lung regions are estimated based on the salient value of each sub-region. Finally, the boundaries of intended regions are smoothened by cubic spline interpolation. This method is accurate and fast.

V Badrinarayanan et.al[15] proposed a deep convolutional encoder-decoder architecture for image segmentation. This is a semantic pixel-wise segmentation. There is a core trainable segmentation engine consists of an encoder network. Then the corresponding decoder network is followed by a pixel-wise classification layer. The decoder network maps the low-resolution encoder feature to fully input the resolution feature for pixel-wise classification.

A Dallal et.al[16] proposed a deep convolutional neural network framework for lung field segmentation from chest radiographs. The proposed network consists of 5 convolutional layers and one fully-connected layer. This is the first method of segmentation in a deep convolutional neural network. Here the selected patch size is around 15% of the original image. This window size provides enough information to the algorithm for the accurate classification of the center pixel. The proposed method provides 98% accuracy,99% sensitivity, and 99% specificity.

Narasimha Raj Kasu and Chandran Saravanan[17] proposed ostu's and K-means clustering methods for the lung segmentation. There are two approaches in segmentation, they are, discontinuity based and similarity-based.In a discontinuity based method, identify the isolated points or lines or edges in an image. In similarity-based segmentation, the similar intensity values in the image are grouped together. Different operations in this approach are clustering, thresholding, region growing, region splitting and merging. There are two evaluation metrics, they are, Jaccardian similarity coefficient and Dice's coefficient(DSC).

A. A Novikov[18] proposed a fully convolutional architecture for the multiclass segmentation of chest radiographs. The proposed architecture consists of subsampling, exponential linear units, highly restrictive regularization and a large number of high resolution low-level abstract features. This model makes use of a multiclass configuration. This method achieved high overlap test scores on JSRT public database. The overall performance of the system can be improved by using exponential linear units.

H Oliveira et.al[19] proposed a deep transfer learning for lung segmentation from chest radiographs. Deep learning has been used for the detection and diagnosis of diseases from different medical images but the portability in this method is limited. This problem is addressed by proposing a novel method for cross dataset transfer learning in chest radiograph based on unsupervised image translation architecture. The accuracy of this method is around 90%. But this method has a disadvantage that, extended training time for the translation.

A Mittal et.al[20] proposed a fully convolutional encoder-decoder network for segmenting the chest radiographs. The encoder-decoder network used here has to skip architecture. This architecture solves the vanishing gradient problem and helps in the feature reuse. The modified upsampling layers are used by the decoder network. The decoder-encoder network achieves regularization and avoids overfitting by make use of dropout layers. The accuracy provided by this method is 98.73%.

J Wang et.al[21] proposed an instance segmentation of anatomical structures in chest radiographs. Here mask R-CNN is used for the instance segmentation. This method is to distinguish the right lung from the left lung and right clavicle from the left clavicle. That is, this method detects and segment all region of interest simultaneously in the image. This is efficient and simple. This method doesn't need post-processing. The accuracy of this method is 97.6%.

J C Souza et.al[22] proposed an automatic lung segmentation based on deep neural networks. This has two deep convolutional neural network models consist of four steps. They are image acquisition, initial segmentation, reconstruction, and final segmentation. The main challenge in segmentation is the overlapping of lung regions due to dense abnormalities. The proposed method addresses this problem by reconstructing the lung regions lost due to different abnormalities. This method has an accuracy of 96.97%, specificity about 96.79% and sensitivity about 97.54%.

3. CONCLUSION

Segmentation is the prerequisite step in computer vision. Segmentation requires classification of pixels. It is also considered as a pattern recogonition problem. In medical imaging the variability in the data is high, so pattern recogonition techniques provides flexibility in segmentation. Another segmentation approach is based on deformable models that is considerably different from fundamental techniques and pattern recogonition methods. One of the disadvantage of this method is, it can converge to a wrong boundary. Gradient vector flow fields can solve this problem. The presence of various structures with different properties in the medical image suggests the use of a specifically designed sequence of multiple segmentation techniques. So a hybrid approach designed for fully automated segmentation of medical images.

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