**Survey: Segmentation of Anatomical Structures in Chest Radiographs and Detection of Cardiomegaly**

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## 1. Introduction

The chest radiograph method is based on X-ray lights and is used for projection of the chest region. This region includes the lungs, heart, ribs, and clavicles. For detection of different problems like lung modules, cardiomegaly, etc. from these images, it is important to segment anatomical structures into the chest. In this survey paper, first, we will focus on the segmentation of the structures in the structures and then, we will explain how cardiomegaly can be detected based on these segmented structures.

## 2. Commonly Used Methods

### *2.1. Rule-Based Methods*

One of the first approaches to segmentation is rule-based algorithms based on image processing techniques like filters, region growing, edge detection algorithms, etc. One of the studies tried to segment lungs by using thresholding (according to histogram), edge detection with gradient analysis, and a post-processing phase that smooths the detected edges [1].

Some of the old methods for segmentation are active appearance [2] and active shape models [3]. These methods are mainly based on a mathematical representation of the desired object's shape. Researchers extract a mathematical model of the shape of the objects by using existing samples and by searching, they try to fit the extracted model on the true object in the image based on the texture feature of the image. This method was used for the segmentation of anatomical structures in the past.

### *2.2. Machine Learning*

Pixel classification is another approach to segment structures in the chest radiographs. Based on the intensity values of a pixel and extracted features based on the relation between the pixel and its neighbors, researchers extracted a feature vector to represent each. These features identify the intensity, local difference, and local texture features of each pixel. After that, by using the training data, they train a linear discriminator or a neural network to classify each pixel in a chest radiograph image according to the corresponding structure [4].

### *2.3. Deep Learning*

One of the studies has tried a very new approach for both suppressing the bones and segmenting the organs by a multi-task deep learning model. The model is referred to as pix2pix multi-task dilated generator (MTdG). This method separates one chest radiograph into two images; bone-suppressed image and organ-segmented image. The architecture of this algorithm is based on a conditional generative adversarial network. One motivation of the work is to execute two tasks simultaneously with one deep network, and the other is to do it by improving efficiency and accuracy. The accuracy of the algorithm is higher than the U-net and one task pix2pix algorithms. There is one downside to this, it requires 6 times more iterations than U-net and 1.2 times more than the one task pix2pix algorithm [5].

### *2.4. Combined Methods*

There are also combined methods for segmenting the clavicle. One of the approaches uses pixel classification (PC) with active shape modeling (ASM) and combines it with dynamic programming (DP). This combined algorithm structurally uses these methods to improve the accuracies of the separate algorithms. Pixel classification is the basis of the approach, and it works as explained in the previous paragraph. ASM is used for creating a reasonable shape (also explained in the previous paragraphs), and DP is used for finding the precise boundary. There is also a disadvantage of using ASM. The mechanism that creates the reasonable shapes also causes it to decrease the accuracy of predicting the borders of unprecedented instances. This research concludes that combining several existing methods can help to handle unclear inputs [6].

Another way that facilitates heart and lung segmentation is bone suppression. One of the approaches for that is filter learning based on regression. This approach aims to separate the frontal chest radiograph into two images; a bone image and a soft-tissue image. To acquire this separation dual-energy imaging is used, which means using a second image that is obtained with a lower energy degree. Dual-energy imaging is only used for training the algorithm, later it can estimate without the requirement of it. There are mainly two different approaches for this problem, local and global models. They both have advantages and disadvantages. The local model has much fewer degrees of freedom to form local patches, but also its accuracy is not as consistent as the global model [7].

## 3. Detection of Cardiomegaly

One of the usages of the segmented structures is the detection of cardiomegaly. In 1991, Nakamori and colleagues investigated effective measurements for the detection of cardiomegaly [8]. From each image, they extracted features like heart area, long and broad diameter, perimeter and height of heart, cardiothoracic ratio (width of the heart / width of the thorax), and the ratio of heart area to thoracic area. They used multivariate analysis and observed ROC curves of each feature according to cardiomegaly to decide effective features. According to them, the most effective features are cardiothoracic ratio and heart area. Their study is one of the most important studies for constructing a rule-based approach to the detection of cardiomegaly for both clinical examination and computer-based detection and has still been used. In addition to that rule-based approach, there is a recent study that uses deep learning techniques to detect cardiomegaly [9]. With the power of neural networks, in addition to detection, they also can classify the chest images according to the level of cardiomegaly disease. Their model can classify the images with 0.88 accuracies.

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