Median Values of Gray Levels for Detection of Lung Contours

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Abstract— **In this paper we discuss about the implementation of Active Shape Model based contour detection algorithm on the digital x-rays of lungs. The effect of considering the mean values while forming the gray level profiles is shown and a modified method where median values improve the result is also presented.**

*Keywords— **Active Shape Model, Contour Detection, Image Segmentation***

I. INTRODUCTION

The process of understanding the contents of image completely relies on Image Segmentation. A successful image segmentation algorithm will be able to clearly separate the object of interest and the remaining part of image, considered as background and till date it remains a fundamental problem. There have been many algorithms developed and implemented which are successful to a limited set of applications. These algorithms vary from the simple 1D method like Otsu's thresholding method to more complex methods [1, 2]. In this paper, we present the variability in the available data, and causes for the non-convergence of the model. The real life images in industry or medical domain exhibit a large variability both in the objects shape as well as the gray level distributions around the model points. In the first part, the method proposed first by Cootes et al [3], known as Active Shape Model (ASM), which resembles Active Contour Models of Kass et al, is explained. The ASM has the advantage that, the shapes vary only in accordance with the variability available in the training set. It is evident that the objects though belong to the same class, exhibit variation in appearance, the causes being lighting, pose or distance etc.

II. ACTIVE SHAPE MODELS

Here is a brief description of the Active Shape Models. These models, which are an average of many typical example shapes obtained from the set of training images, will guide the detection of shapes in a given target image. A set of points on the boundary of the objects are required to describe the shape on an image. The correctness of these points which are manually marked, and the statistics of such points is captured by the shape model, are crucial since the model and hence the detection process is based on them. Thus care is to be exercised in identifying and marking the points. The boundary of the object is marked by ***n*** points on all the ***N*** images of the training set. The number ***n*** is selected such that they are adequately able to represent the shape. These ***n*** points can be described by a vector $\mathbf{x} = (\mathbf{x_1}\ \mathbf{y_1},\ \mathbf{x_2}\ \mathbf{y_2},\dots,\ \mathbf{x_n}\ \mathbf{y_n})$, where $\mathbf{x_i}$ and $\mathbf{y_i}$ are the coordinates of the i^{th} point. As described by the Cootes algorithm, the mean of all the annotated points is calculated by

$$\bar{\mathbf{x}} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{x_i}$$

and its corresponding covariance matrix **S** will be

$$\mathbf{S} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{dx_i}\mathbf{dx_i^T}$$

where

$$\mathbf{dx_i} = \mathbf{x_i} - \bar{\mathbf{x}}$$

which is the deviation of each of the $\mathbf{i}^{th}$ shape from $\bar{\boldsymbol{x}}$.

The dimension of the obtained data set can be reduced by retaining only the most significant Eigen vectors corresponding to the largest Eigen values. Different shapes can further be generated by using $\mathbf{x} = \bar{\mathbf{x}} + \mathbf{Pb}$, where $\mathbf{P}$ is the matrix of retained Eigen vectors and **b** a vector of weights. The matrix $\mathbf{P}$ is generated by Principal Component Analysis (PCA), where the dimension of the data set is reduced, and the largest Eigen values correspond to the principal axis.

III. IMAGES AND METHOD

Active contours are built on the statistics of the coordinates obtained from the basic training set of images, which will contain many possible variants of the objects. The model thus built is capable of representing the objects completely. The Point Distribution Model (PDM) for the case of lungs is shown in figure 1. The images are taken from the JSRT database [4, 5]. Each image is annotated and for building this PDM we considered a set of 30 images.

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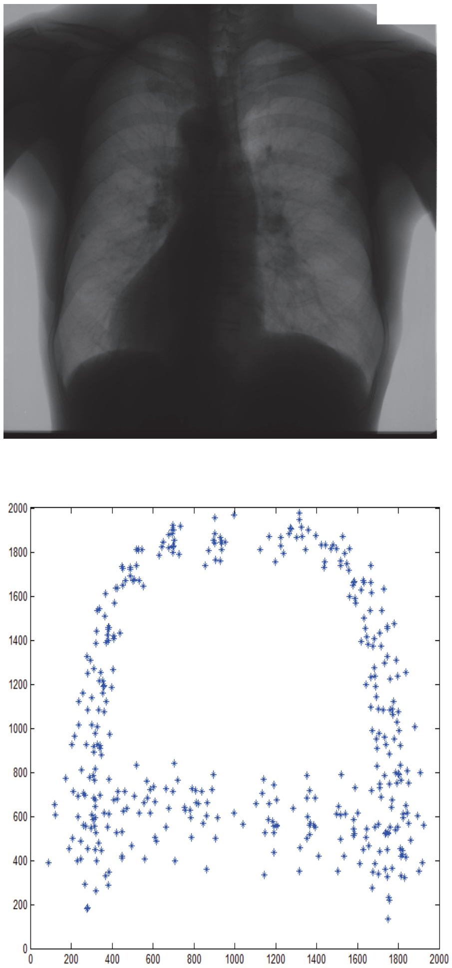


Figure 1. A typical digital x-ray of the posterior anterior lungs. The PDM generated by the all the annotated images.

At every model point thus obtained, a profile model is generated, describing the gray level distribution around the point. The length of the profile n_p , was fixed as 82 on either side of the contour point, and perpendicular to it. The ASM algorithm iteratively searches for the best matching point along the perpendicular to the target contour. At every step, the Mahalanobis distance between the mean shape and the latest found shape is calculated. The optimum position gives the best fit object.

But the ASM requires a large set of images for training, and needs initialization. If the initialization is wrongly initiated, then the entire search process may never converge. In our work, the initializations have been the same as the mean shape of the lungs.

IV. MEDIAN VALUES FOR GRAY LEVEL PROFILES

While modelling the gray levels, around the annotated points, in the original ASM method, a normalized derivative profile is built for every landmark point and then its mean, denoted as $\boldsymbol{y}_j = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{dg}_{ij}$

where $d\mathbf{g}_{ij}$ is the derivative profile of length (n_p - 1). The figure 2 shows the gray levels at an annotated point, corresponding mean on the same plot.

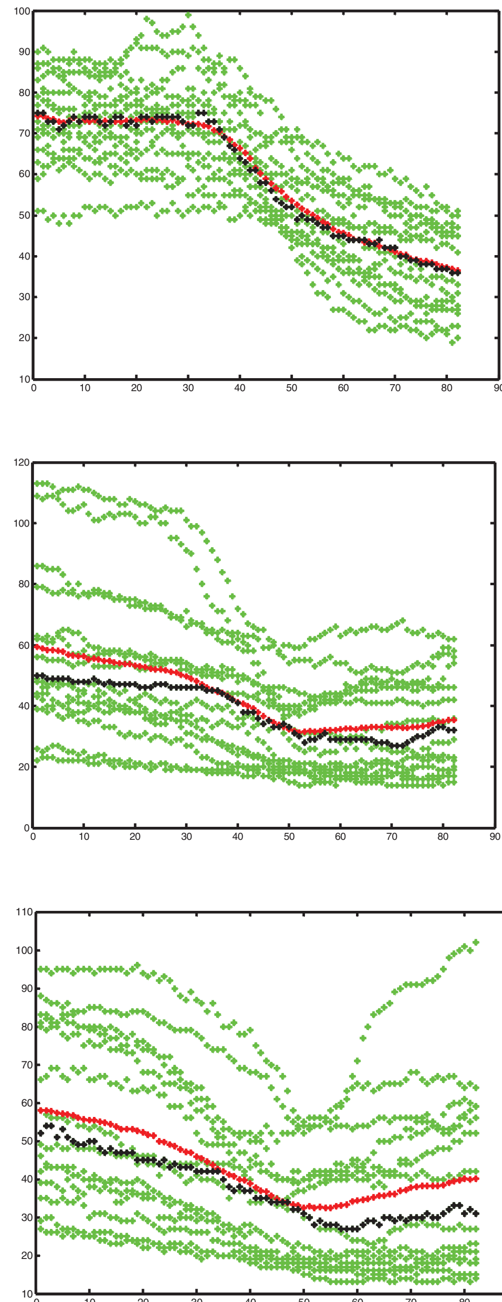
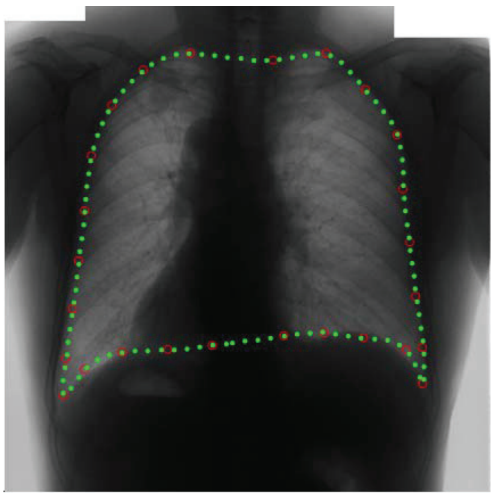


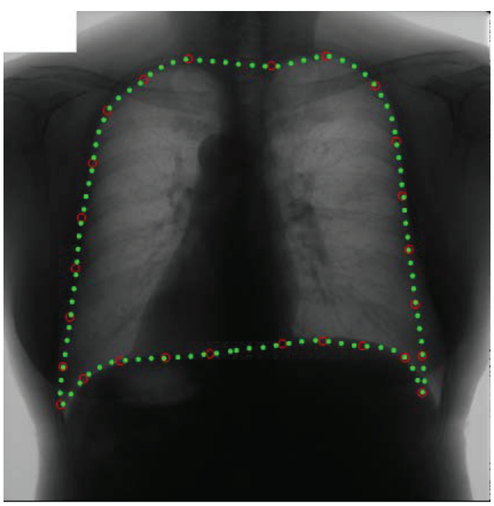
Figure 2. Gray levels at a common point from the training images are shown in green; Mean of all values is in red and Median in black.

We make a change here, by considering the median of all the gray level profiles obtained, instead of mean. By doing so, the problems of outliers can be overcome. These outliers may arise due to wrong annotation or large data variability, but not all of them will be contaminating the data. As can be seen in the graph below, the presence of the outliers may shift the mean profile model, which will further lead to a wrong point being selected as the contour point. But when median of the profile is selected, it is much more stable. Literature is full of material as to how to deal with outliers [6], which range from eliminating the outliers altogether to, developing methods which are immune to the presence of outliers[7].

V. RESULTS

Some example images where the detection of the contours of the lungs is achieved by ASM are shown in figure 3. The code has been implemented in MATLAB.





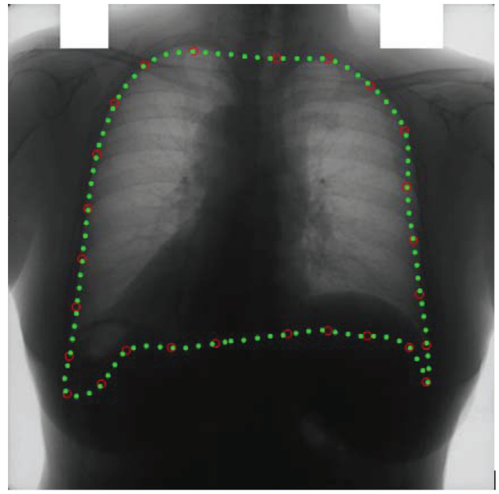


Figure 3.Some examples of the images showing the detected lung contour.

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