LUNG CONTOUR DETECTION

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I. Introduction

Chest radiographs can help the detection of lung cancers, TB and other lung diseases. The early detection of cancers is very important as it significantly increases the chance to cure the disease.

Global screening is a relatively cheap way to detect breast cancers and TB. It is available in many countries including Hungary. Unfortunately such screening programs generate a vast amount of pictures to be analysed by experts. This is where computer-aided detection (CAD) can help the work of radiologists.

CAD systems are not reliable enough to do the work alone at the moment. The current goal is only to create a system that can help the detection and increase the accuracy of examination by searching suspicious areas (region of interest, ROI) or by enhancing the visibility of the picture at the darker regions. The first step in such an evaluation would be the delineation of the organs' boundaries. Searching the contour of the lung, the heart, the clavicles and the ribs determine the area of processing and the raw data for image enhancing. The lung contour has diagnostic value without further processing too as it can show cardiomegaly and pneumothorax.

II. Lung contour detection

Several methods have been developed to search the contour of the lungs. The problem is not easy as the pictures are sometimes noisy and different parts of the body overlap on the x-ray images. Edges of the ribs and the clavicles and the boundaries of the breasts make the contours less clear and add further edges making proper contour detection more difficult.

Some algorithms try to get the lung area by classifying each pixel. Information of the surrounding texture, the position of the pixel and the classification of neighbouring pixels can be used. These methods usually use *neural networks*, *support vector machines* or *kNN-classifiers*. After getting a rough result from these algorithms further processing is usually needed to get lung-like results by making the area connected and avoiding holes.

Another group of algorithms concentrate on the contour only. These are usually *snake*-like methods [1]. They start from an average contour and move contourpoints to fit the actual shape in each iteration. The measure of the goodness is an energy function of two parts. One is responsible for the global shape (for example by avoiding high curvature contours) and the other fits the shape locally, usually by finding the maximum of some kind of gradient.

These learning methods need great number of pictures evaluated by experts. Drawing the contours in hundreds of images is a big work and thus usually only a limited number of denoted pictures are available for the algorithms. We used the publicly available reference image database of 247 radiographs by the Japanese Society of Thoratic Radiology [2]. The delineation of these pictures was made by the research group of van Ginneken [3].

ASM [4] can be seen as an extension of snakes. It generates the global and local part of the energy function automatically from a statistic model and defines a search algorithm too.

It groups contour landmark points of each training picture into one vector and applies PCA on them. The first few eigenvectors belonging to the largest eigenvalues are chosen to describe the shapes. The actual contour is computed from the chosen eigenvectors and the mean shape. The weights of the eigenvectors are limited and this gives a restriction on the allowed shapes. Procrustes analysis [5] can be used before the PCA to align shapes. This makes the shapes independent of position, orientation and size. An example can be seen on Figure 1.

The local fitting is done by building gray-level appearance models at every contour landmark point. These are built from normalized gradient vectors sampled from both sides of the line perpendicular to the contour. Mahalanobis distance [4] is used to choose between different profile candidates.

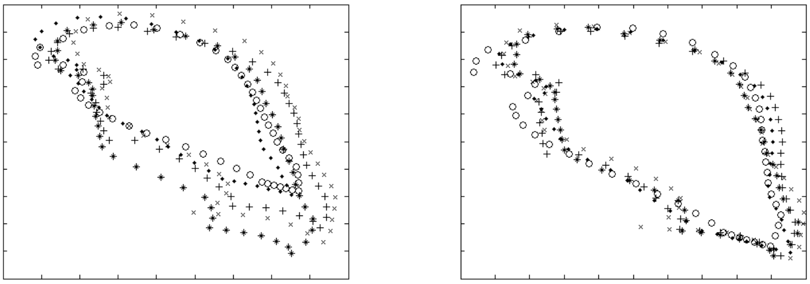

Figure 1: Lung contours without alignment (on the left) and after Procrustes alignment (on the right)

To make the search space smaller, landmark points are moved perpendicular to the contour one by one and the best fitting to the local appearance model is chosen. After a few iterations this process usually converges to a contour.

All these steps are repeated at different resolutions, starting from the coarsest. At a finer resolution the search is continued from the previous contour result. This multiresolution method helps keeping both the computational cost and the contour error low.

III. Results and Conclusion

Test runs show that ASM gives good results compared to ad-hoc algorithms. Over 80% of the test pictures were evaluated without major errors. In these cases the contours were not only a rough approximation of the ideal solution, but they were highly accurate. Most of the errors occur at the early phase of the algorithm, at coarser resolutions.

The solution for this problem could be to use information of the fine resolution pictures too at the early phases or to use more complex texture information instead of the simple gradients.

Another way to improve results is using active appearance models (AAM). AAM combines texture information of the object with the shape information of the contour. This combination highly increases the robustness of the algorithm at the price of higher computational costs.

References

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