AUTOMATIC RIB DETECTION IN CHEST RADIOGRAPHS

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ABSTRACT

This paper presents an overview of an algorithm for rib detection in chest x-rays. The goal of the algorithm is to return the location of the borders of the ribs to a screening system to enable intercostal spaces to be extracted and analysed.

The detection of objects in pictures can usually be separated into two steps: image enhancement and feature extraction. The amount of computation required by our algorithm is minimized by processing only that information which is required to achieve the goal of the algorithm, and by using knowledge of the structure of the rib cage to ?uide the extraction of the rib borders. In par-ticular, significant reduction in computation is achieved by avoiding the enhancement of the entire picture. In addition, not all points in the image need be considered as possible rib border points, nor do all points on each rib border need be detected .

The rib borders are returned to the screening system as second degree polynomials. Results or testing the algorithm for a set of chest radiographs are illustrated by superimposing the detected rib borders onto the X-ray images.

1-1 Previous Work

The existing algorithms for automatic rib detection by Toriwaki (Tor-73A). Wechsler (Wec-75A, Wec-75B) and Persoon (Per-75) have all taken the approach of first preprocessing the entire image by global operations to enhance it and then finding all the points on each rib border.

If these algorithms are considered carefully, it becomes apparent that much of the computation done by these three methods is not necessary. In all three algorithms, every point on each rib border is, at sometime, located. As each border is represented by a low order polynomial, only a small number of points need be located on each curve. Furthermore, performing an operation on the whole picture or considering all points as equal candidates for rib borders is both unnecessary and expensive.

2-1 Overview of the Algorithm

Detection of the rib borders procedes separately for each lung. The initial step locates the lower border of two adjacent ribs in the upper middle portion of the lung field; the average width of one of these starting ribs is also calculated. The next step selects vertical slices through the lung field, enchances them, and detects rib border points. The location of the two starting ribs and the average rib width is used to guide the search on each slice for the remaining ribs. When border points have been detected on all slices, they are linked together to form a set of points for each rib border. Finally, second degree polynomials are fitted to each border.

2-2 Detectin, of the. Starting Ribs,

In order to determine candidate areas for the detection of all the rib borders on each slice, two quantities are required: 1) the distance between two adjacent ribs and 2) the average width Qf one of these ribs.

An extensive search for the starting ribs is necessary because 1) the starting ribs must be accurately found in order to provide information for the selection of candidate areas for the remaining ribs, and 2) there is no prior knowledge about their expected positions or width to guide the search. The detection of the starting ribs proceeds in the following 5 steps:

*i) T*he Area of Search Is Selected

A section of the image is chosen which lies midway in the lung field between the bottom and the top of the lung. The section is 128 columns wide and 64 rows high (the original image is 256x256): this covers an area of the image "from the mediastinum to the outside of the thorax and is large enough to include at least two complete rib images.

ii) The Selected Area Is Pre-processed

The selected region is pre-processed using hysteresis smoothing (Dud-74). The smoothing window height is chosen dynamically via an analysis of a grey level distance histogram.

iii) Detection of Possible Rib Borders

A funcion, MRIB, is applied to each of the smoothed columns. MRIB measures the amount a given interval on a slice corresponds to a rib image, by comparing the average grey level within an interval with that outside the interval. MRIB is applied using a range of potential starting points and rib widths. Essentially MRIB behaves like a correlation function.

iv.) Linking Two Sets of Border Points

The number of possible border points occurring at each of the 64 rows of the section is calculated, Two of the rows, R1 and R2, are selected as the rows containing the largest number of possible border points provided that these rows are between 10 and 30 rows apart. R1 and R2 are assumed to occur at the peaks in the curves of two adjacent ribs.

Two sets of points are formed as the lower border points of the two ribs. The first points entered in each sets are those possible border points in smoothed columns which are closest to R1 and R2, respectively, The remaining points in the sets are selected from the possible border points in columns that are closest to the previously selected points.

v) Calculation of ttig. Average Rib Width

The set of most likely widths of ribs is averaged to obtain the width of one of the starting ribs.

2rl Detection of Other Ribs

The other ribs are detected by searching above or below already known rib borders in an area in which the next rib is expected to be located. Relationships between inter-rib spacings have been demonstrated by Persoon (Per-75), and verified by us. The rib border points are found on a number of vertical slices through the lung fields. The slices are spaced several columns apart as not all points on the rib border are

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necessary.

3-1 Experiments

Our rib detection algorithm has been used to detect ribs in several chest radiographs. These X-rays show a variety of qualities, both in disease state and in film quality, To illustrate the results of the algorithm, the detected borders have been superimposed onto the image. Figures 1a-1c show each radiograph; Figures 2a-2c show the same x-ray with the rib borders superimposed.

As can be seen in the illustrations, the algorithm is fairly successful for good quality films; usually 7 pairs of ribs are detected. Failure to detect a rib has five main causes:

1) The clavicle. Because the image of the clavicle is similar in nature to the rib images and crosses the ribs at the top of the lung, rib border points are sometimes chosen which are actually borders of the clavicle. This occurs more frequently in images with very dark lung fields, such as in the image shown in Figure 1-c, where the clavicle is more visible than the ribs.

2) The diaphragm area. If the bottom rib is close to the diaphragm, or the diaphragm does not have a sharp border (Figure 1-c), points may be detected in the diaphragm instead of at the ribs or the points may be missed. In addition, if breast tissue is present in the X-ray then points may be detected in that tissue near the outside of the thorax rather than on the rib below.

3) The heart border. The actual edges *of* the heart may be sufficiently lower in gray level than the estimated white value to allow some border points of the heart to be detected as rib borders, These points usually lie close enough to the actual ribs to be included as border points but far enough away to make the curves representing the ribs inaccurate.

4) Dark areas. If some of the ribs are not distinguishable in very dark lung fields, then several border points may be missing from those ribs. If there are large gaps in the ribs then the sets of border points may be incorrectly linked and the resulting curves may be inaccurate or unacceptable, This is the cause of missing rib borders in Figures 1-b and 1-c.

5) Disease. If disease obscures the ribs then border points may be missing or inaccurate, The algorithm is able to overcome tumours which do not completely obscure the ribs but performs poorly when a large amount of disease is present as in Figure 1-c. In such cases the ribs are not visible anyway and the X-ray should be considered as abnormal.

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Figure 1-a

Figure 1-b

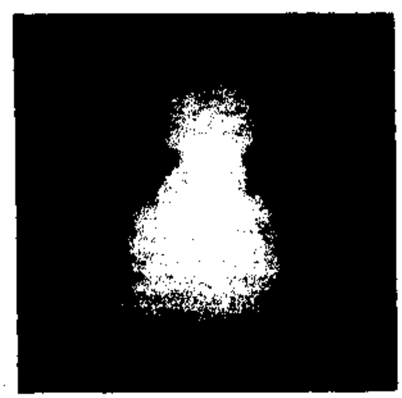

Figure 1-c

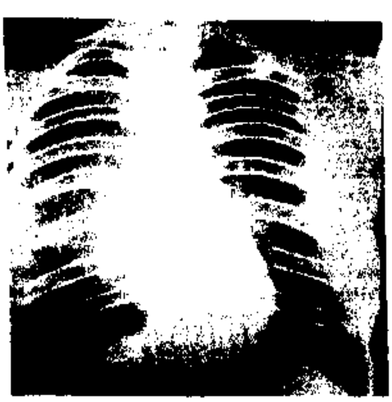

Figure 2-a

Figure 2-b

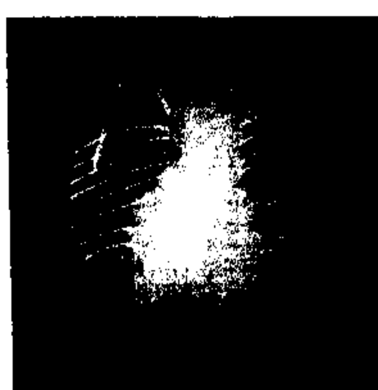

Figure 2-c

KNOWLEDGE-BASE DRIVEN ANALYSIS OF CINECARDIOANGIOGRAMS

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This short note describes research into the application of AI techniques to the analysis of cinecardioangiograms. These are X-ray films of the heart taken while a radiopaque dye is injected into the heart cavity. The film shows the opacified blood inside the left ventricle, thus outlining the inside wall of the cavity. The problem is to build a knowledge base which can guide the analysis of the motion of the walls in these films, determine the various parameters which physicians use in their diagnoses and recognize abnormalities of heart wall motion.

This research is being done in conjunction with the Cardiovascular Unit at Toronto General Hospital. The role of the medical experts is to provide the knowledge necessary for construction of the knowledge base and, to evaluate the performance of the system we produce.

Another aspect of the project is to develop front and back ends to the knowledge based system. The front end consists of a digitizer for the films, and a picture processing module which can accept guidance from the higher levels of the system. The back end includes displays for the information determined (graphs and movies of what the system recogni zes).

Now that the overall scope of the project has been outlined, let us look a little more closely at the knowledge-based understanding part. The general methodology is based on work by Badler [1] and Tsotsos [21. The low level part has the following features: i) it implements a basic independent algorithm for determining the heart wall border (Freuder [3] has a similarly built low level); ii) it can accept advice from the higher levels of the system on where to look for a border (this is useful for following around the border once its motion characteristics have been roughly determined); iii) it asks the high levels for verification as to whether a particular section of proposed border really does belong to the border; iv) when it thinks it is lost, it asks the higher levels for re-orientation; v) it can communicate with the higher levels of the system while running in parallel with and independently of the remainder of the system. A system with these characteristics has already been implemented (Reeves and Buxton [4]).

The remainder of the system simulates the motion of the left ventricle using a 3-D thick-walled patch model, and uses this model to guide the low level. Each patch is an instantiation of one of several heart muscle frames (Minsky 15]). Such a frame defines the properties of the patch during a heart cycle: shape and size changes (note that the constructs for the representation of these concepts were not handled by Badler [1] and Tsotsos [2]); velocity and trajectory information; normal and abnormal motions with tolerances. Such information is clearly dependent on the actual heart viewed and on the patch location within the wall. It is hoped that such information can be derived from the model using the fact that the contraction of muscle fiber generates a force - but the knowledge of medical researchers on this is very limited and thus this may be hoping for a bit too much.

Using this 3-D model the location of the border is predicted, image by image, by simply using the angle of the X-rays (which is known) incident of the heart and taking a projection on this plane. This information is then used to guide the low level. The low level returns the actual borders found and the model is perturbed to fit this data. During this process, various parts of the patch frame (sub-frames) are activated to account for abnormal or unexplicable motion.

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