Detection and Compensation of Rib Structures in Chest Radiographs for Diagnose Assistance

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ABSTRACT

We developed a new method to compensate the rib structures in digital x-ray images. The intrinsic information of rib structures is eliminated and a higher image quality for the diagnosis of pulmonal structures is achieved. An essential task of the algorithm is the robust detection of the rib borders. In this paper we introduce three algorithms to perform this task. The first, introduced by SCHRECKENBERG and JOSWIG\textsuperscript{1}, uses the hough transform to find rib borders, the second one uses a synergetic classifier to estimate the matching between rib edge templates and rib borders. The last one, the sinking lead algorithm, gives the best classification results by performing a matched template technique in combination with partial methods from the former two algorithms.

Keywords: chest radiographs, rib detection, rib compensation, sinking lead algorithm, matched template, snakes, synergetics

1. INTRODUCTION

X-ray images of the chest are an important diagnostic examination in clinical daily routine. On the other hand they are the most complex images gained by x-ray technology and often relevant diagnostic structures are superimposed by other objects like the ribs or the heart. This can conceal pulmonal tumors and other pathologic structures for the radiologist. In clinical studies it has been proven, that images without those superpositions are better suited for differential diagnosis. Our method results in images without such rib structures where the x-ray reduction of rib structures is eliminated and a higher image quality for the diagnosis of pulmonary structures will achieved.

The first task to be performed is the robust detection of rib borders. A suitable model for the rib borders, which yields for all the three proposed algorithms, is to describe them as parabolas. This is a good approximation to the natural anatomical shape. To describe a rib entirely we use 4 parabolas, two for the left and right borders of the ventral edges and two for the lower and upper borders of the dorsal ribs. In the following the algorithms will be dedicated to the dorsal rib borders as they can be adapted to the ventral ribs easily. Furthermore the algorithms work on one half of the chest image (figure 1). To detect the ribs in a complete chest image the calculations are performed separately for each half and the results are matched.

2. CLASSICAL DETECTION OF RIB BORDERS

The classical approach\textsuperscript{1} works as follows. After a preprocessing step which takes the logarithmic characteristics of the x-ray source into account, a global edge detection is performed. This is done by applying a filter operation in the frequency domain to emphasize the high frequency parts of the image signal. As mentioned before the rib structures are approximated by a set of parabolas. \textit{In praxi} this has been proved to be a suitable model. By applying a hough transform on the image the edges can be determined. The disadvantage of this method is the difficulty of parameter selection for the hough transform, which is not transparent and makes it impossible to run the algorithm automatically.

The first step is to generate 16 rib border templates (figure 2) and to calculate the cross covariance with a shrinked matrix of the image of the chest half. The cross covariance is defined as follows

\[
CCR(x, y) = \frac{\sum_{k,j} b(x + k, y + l) - b^*(x - l) (t(k, l) - t^*)}{\sqrt{\sum_{k,j} (b(x + k, y + l) - b^*)^2 \sum_{k,j} (t(k, l) - t^*)^2}} \tag{1}
\]
In this equation $b$ represents the chest image, $t$ the rib template and $b^*$ respective $t^*$ the exspection value of the grey levels in $b$ and $t$ respectively. The cross covariance therefore gives a maximal edge quality value (correlation coefficient) $g$ and the associated edge direction for each pixel. They build two new images as shown in figure 3.

From these two images the edge images for the upper and lower dorsal rib edges and the left and right ventral edges now can be generated. Therefore in the edge direction image (figure 3 (right)) upper dorsal and lower dorsal edges are in a very close neighborhood. The parabolas from the dorsal lower edge image are therefore not necessarily parabolas that describe lower rib borders. For this reason in the following we distinguish only between dorsal and ventral rib parts. The normed cross covariance is not calculated with the original chest image but after performing a low pass filtering.

In a second step structures which look like parabolas have to be detected. This is done by a modified hough transformation for second order equations. A parabola can be described by the following equation:

$$y = ax^2 + bx + c$$  \hspace{1cm} (2)

Usually $a, b$ and $c$ are given to calculate the parabola. Here, $x$ and $y$ are given and for resolution we have to vary $a$ and $b$ for each position $c$ in the image.

$$c = y - ax^2 - bx$$  \hspace{1cm} (3)
For each pixel at position \((x, y)\) we get a set of triples \((a, b, c)\). The variations for \(a\) and \(b\) that define parabolas representing rib borders can be restricted strongly to specific values. For each of the triples \((a, b, c)\) the value \(AS(a, b, c)\) in the three-dimensional accumulator space is incremented by the corresponding quality value \(g(x, y)\). By searching maxima in accumulator space we get a set of candidates for rib corresponding parabolas (figure 4).

The parabolas found by the hough transformation are only potential candidates for the correct matching with the rib borders. Therefore it is necessary to perform a suitable postprocessing of the so determined rib border candidates as due to noise in the chest image not every detected parabola corresponds with a rib border and vice versa.

Some efforts have been made to perform this post processing, but they have not been very successful.\(^1\)\(^2\) Other are not applicable in praxis.\(^4\) The methods proposed by Schreckenberg, Joswig\(^1\) and Lesch\(^2\) are limited to the deletion of parabolas which have parameters that are not within a heuristic determined parameter interval. The insertion of parabolas is mentioned but no method is described how this could be done. Yue introduces a set of quality metrics for rib border candidates.\(^5\) Our experience with the proposed methods is that they are reasonable in theory but less effective in praxi. So it is proposed e.g. in the case of a crosssection of two parabolas to delete the parabola with a lower quality in accumulator space. In praxi this seems often be the wrong selection as correct detected edges (parabolas) tend to have a lower quality in accumulator space. This effect is a consequence of the discretization step of the accumulator space and noise in the original chest image. In a following section we therefore handle the problem of the selection of wrong parabolas and the insertion of missing rib borders.

3. SYNERGETIC DETECTION OF RIB BORDERS

Now we present an alternative algorithm for the detection of the rib borders. To emphasize the high frequency parts of the image signal, which will mainly correspond to the rib edges, an unsharp masking is performed with a global edge detection as postprocessing. Again the key idea of the approach is to approximate rib structures by a set of parabolas. By applying a hough transformation on the image the edges can be determined as shown in the former section.
The cross covariance of a shrunk image with edge templates (figure 2) is performed to determine the pixels which correspond to rib edges.$^1$ Better results concerning robustness and performance of the procedures could be obtained using synergetic classifiers with edge prototypes which leads to higher performance and accuracy.$^3,^2$

Synergetic classifiers have properties that are very useful for this identification task:

- Independence concerning brightness and contrast
- The learning process is unsupervised
- Only one adjoined prototype is necessary per class
- Adaptivity, which means, the classifier learns during classification
- Scaling independency
- Translation invariance
- Orientation invariance

A short description of the synergetic classification algorithm is now given by a rather simple example for letter recognition (figure 5).

The prototype vectors are

$$\bar{v}_k = \begin{pmatrix} v_{k1} \\ \vdots \\ v_{kN} \end{pmatrix} \quad k = 1, \ldots, M. \quad (4)$$

$M$ is here the number of classes. The prototype vectors are assumed to be normalized and of zero mean:

$$\sum_{i=1}^{N} v_{ki} = 0 \quad \text{and} \quad \sum_{i=1}^{N} v_{ki}^2 = 1 \quad \forall \bar{v}_k \quad k = 1, \ldots, M \quad (5)$$
Figure 5. Prototypes (left), adjoined prototypes (center), letters to be classified (right)

A set of adjoined prototype vectors $\bar{v}_k^+$ is computed which satisfy an orthonormal relation:

$$ (\bar{v}_k^+, \bar{v}_l) = \delta_{kl} $$  

(6)

The adjoined prototype vectors are linear combinations of the prototype vectors and can easily be computed by solving a linear equation system.

$$ \bar{v}_k^+ = \sum_{i=1}^{M} a_{ik} \bar{v}_i. $$  

(7)

According to HAKEN the pattern classification can be seen as a dynamic process similar to the movement of a mass point in a potential field.\(^3\) The potential field has the following form:

$$ V = \frac{1}{2} \sum_{k=1}^{M} \lambda_k (\bar{v}_k^+, \bar{q})^2 + \frac{1}{4} R \sum_{k \neq l} (\bar{v}_k^+, \bar{q})^2 (\bar{v}_l^+, \bar{q}) + \frac{1}{4} C (\bar{q}^+, \bar{q})^2 $$  

(8)

In the field of pattern analysis the classification process can be reduced to the calculation of the product of the adjoined prototypes with the vector to be classified. Mathematically this reads as follows:

$$ |(\bar{v}_j^+, \bar{q})| = \max \{|(\bar{v}_j^+, \bar{q})|\} \quad j = 1, \ldots, M $$  

(9)

The results of the classification for the letter recognition example given above can be viewed in the following table:

<table>
<thead>
<tr>
<th></th>
<th>Expl1</th>
<th>Expl2</th>
<th>Expl3</th>
<th>Expl4</th>
<th>Expl5</th>
<th>Expl6</th>
<th>Expl7</th>
<th>Expl8</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP with A</td>
<td>0.40</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.12</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
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<td>0.00</td>
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<td>1.00</td>
<td>0.23</td>
<td>0.07</td>
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<tr>
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<td>A</td>
<td>B</td>
<td>A</td>
<td>B</td>
<td>A</td>
<td>B</td>
<td>B</td>
<td>B</td>
</tr>
<tr>
<td>Classified</td>
<td>A</td>
<td>B</td>
<td>A</td>
<td>B</td>
<td>B</td>
<td>A</td>
<td>B</td>
<td>B</td>
</tr>
</tbody>
</table>

The synergetic classification of rib borders is obtained with four classes. By using the edge templates from figure 2, two adjoined prototypes (figure 6) are determined.

The use of synergetic classifiers allows the use of much more templates than shown in figure 2 to generate prototypes from x-ray images, which lead to better classification results. The higher performance results from the fact that for cross-covariance four templates per search direction are necessary, whereas the synergetic classifier works with one adjoined prototype per direction.

The scalar products from the synergetic classification are used as input for the hough transformation. An example for rib border parabolas is shown in figure 7.
4. IMPROVEMENT OF RIB DETECTION RESULTS BY POSTPROCESSING

In this section we first describe the knowledge based selection of correct classified rib borders from the set of candidates found by one of the above described rib border detection algorithms.

In a first step we look for deviations in the set of parabolas. These are parabolas which significantly differ in at least one parameter from the mean of the other parabola parameters. In contrast to Schreckenberg and Joswig we regard the parabola parameters, not the values in accumulator space of the hough transform. It is not necessary to consider the parameter \( c \) as it only performs a vertical shifting of the parabola in the image. The criterion to select wrong parabolas concerning parameter \( b \) is given in the following equation:

\[
\bar{b} = \frac{1}{n} \sum b_i, \quad \text{with} \quad |b_i - \bar{b}| > \epsilon \quad (n = \#\text{parabolas})
\]  

(10)

Equation 10 is performed analogously for parameter \( a \). Parabolas that do not satisfy this criterion are marked as poor. One result of this operation is shown in figure 8.

Now it is tested if there are gaps in the set of parabolas. If the distance of two parabolas which are neighbors in the image is bigger than the overall rib thickness \( d \), a gap is detected (equation 11).
Figure 8. Elimination of edges marked as poor.

\[ c_{i+1} - c_i > d \]  

Then it is determined if there are any parabolas that are marked as poor before in this gap. The quality criterion is varied for this parabola by increasing \( \epsilon \).

\[ c_1 = \frac{3}{2} \epsilon \]

If the parabola satisfies the new criterion yield by replacing \( \epsilon \) in equation 10 with \( c_1 \) it is marked _good_. Now it is necessary to divide the candidates in upper and lower ribs. For this task we use a rather simple algorithm. The ribs in the chest image are bright structures on a dark background (where dark corresponds with low grey level values in the image). For each point on a parabola the overall value of pixels along a perpendicular line above and below the rib border on this line is calculated. This line is shorter than half of the average rib thickness. The difference between the upper and lower sum of greylevels of this line is a criterion for the parabola being an upper or a lower rib border. If the difference is negative we have an upper rib border and vice versa. This simple algorithm yields very good results in practice. Furthermore parabolas, which have a difference close to zero might be marked as _poor_, as there should be significant differences for real rib borders. The knowledge about upper and lower rib edges allows further postprocessing.

Now it is simple to detect missing rib borders as this is the case if two neighbor parabolas are classified as upper borders respective lower borders. The missing parabola is inserted by copying the corresponding upper/lower rib border to an estimated position in a distance of the average rib thickness (figure 9).

The roughly guessed new parabolas do not fit the rib borders very good in general. The same yields for parabolas from the hough transform. As the accumulator space is discrete, the parabolas are often shifted relative to the real rib borders by one or more pixels. This can be overcome by moving the detected parabolas up and down and calculating the quality metric of the grey value differences. By finding the corresponding extrema of the grey level difference the parabola can be placed in a better position (figure 10).

The problem of crossing rib borders can now be solved (figure 11). If the parabolas of one rib are crossing each other it has to be tested if parameter \( a_i \) of the upper edge \( i \) is bigger than that of the corresponding lower edge. If
this is the case the parabola is deleted and estimated new as missing parabolas. If not, the parabola is deleted which has the biggest difference from all estimated parabola values. The same yields for the two parabolas which describe a rib crossing another rib.

After the described postprocessing has been performed, a method described in the next section to gain a complete rib segmentation which is substantial for a successful compensation of all ribs can be applied.

5. SINKING LEAD ALGORITHM FOR DETECTION OF RIB BORDERS
We developed an alternative method for rib border detection, the "sinking lead algorithm", which performs a kind of matched template technique. This approach integrates a-priori knowledge about the rib borders and allows a fast detection and compensation.

The goal of this algorithm is to generate the parabola candidates for the described postprocessing faster than before with previous mentioned algorithms. During the development and testing of the described hough transform the parameters $a$ and $b$ for over 100 chest images have been determined. This allows to generate a statistic of these parameters and calculate probable values for $a$ and $b$ for parabolas that likely describe a rib edge.

All parabolas that describe rib borders have in common, that their highest point resides on a vertical axis in the middle of the half chest image. In the original chest image we now set parabolas with all possible values (concerning the above mentioned statistic) for $a$ and $b$ sink along this axis. At each step (sinking, varying $a$ and $b$) it is tried to classify the parabola as candidate for a upper or lower rib border as described above. The fact, that upper and lower borders follow subsequently can be taken into account to stabilize this type of classification.

Beyond a significant lower runtime the sinking lead algorithm performs the rib detection in one step without calculating the time consuming and fault sensitive hough transform.

6. COMPLETE DETECTION OF RIB BORDERS
In further research efforts we have developed a method that allows to transform the parabolas into snakes and therefore gain a more accurate rib detection. The found parabolas are interpreted as the initialization for an active contour model. The active contours are part of a complex shape- and scene model we generated.\textsuperscript{57}
Figure 10. Image with new positioned ribs.

This hierarchical model of the chest is similar to that of the hand. With this model the available a priori knowledge about the topology is integrated by calculating a triangularization based shape and scene energy. The ribs are a few of several end nodes within this model represented by active contours (triangulated snakes as in figure 12).

The detected rib borders from one of the three methods described in the further sections can now be used to align this model to the image by matching the found ribs with the corresponding snakes of the model. The minimization of the scene energy leads than to the final segmentation result (a complete segmentation of the relevant chest structures, especially the ribs). This is an essential condition for the following compensation of all ribs.

7. COMPENSATION OF RIB STRUCTURES

Based on an combined anatomical and grey-level model of the ribs the corresponding grey-levels can be subtracted in the estimated areas of the image (figure 13).

The compensation itself is been done using a simple model for the grey level profile of a rib (figure 14). With this model the assumed thickness of the rib for each point within a detected rib is estimated.

With this information the grey level can be estimated that has to be subtracted from the rib grey level.

8. RESULTS

The algorithm has been tested with 154 chest radiographs and in nearly all cases a suitable detection of the rib borders could be performed. As no additional images are necessary the method can be applied to any standard chest radiographs from routine examinations. In some cases manual corrections of the detected rib borders were necessary. The classification of rib borders with synergetic algorithms is four times faster than the classical method. Further speedup and simplification can be achieved using the sinking lead algorithm at the cost of a little loss of accuracy that can be compensated by the use of the active contour model for a complete segmentation.
Figure 11. Left: Chest image with crossing ribs, left: after elimination.

Figure 12. Triangulated model of the chest.

9. DISCUSSION

The proposed method provides a reliable compensation of rib structures and can be a valuable assistance in the radiologic diagnosis of chest x-ray images. The superposition of relevant pulmonal structures with rib structures could be successfully separated. An integration of the method in systems for demonstration of digital images is possible. At this time we are working on a user interface to broaden the clinical evaluation phase.

The key to successful compensation of rib structures is the robust detection of rib borders. An interactive component to correct misclassifications manually has to be added for the few cases where automatic detection can not be performed successfully. In conventional images a sigmoid characteristic curve of x-ray reduction can be assumed. The image material shown here was produced by digital radiography and the assumption no longer yields.
Figure 13. Upper left: original part of a chest image, upper right: part with marked rib borders and a pulmonary lesion, lower left: calculated rib structure normalized to 255 grey levels, lower right: image after compensation.

Figure 14. Rib profile.

This has to be taken into account in further developments.

As no additional images are necessary in contrast to energy subtraction method our approach can be applied on any standard chest x-ray film. The proposed method provides a reliable compensation of rib structures and can be a usable assistance in radiologic diagnosis of chest x-ray images. The superposition of relevant pulmonary structures with ribs can be successfully eliminated.

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