COMPUTER AIDED DIAGNOSIS IN DIGITAL CHEST RADIOGRAPHY:
EVALUATION OF PULMONARY EMPHYSEMA IN COPD PATIENTS

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Abstract: Alterations of the lung shape related to hyperinflation are regarded as indicative of emphysema. We developed and tested a computational descriptor of the shape of the lung-silhouette, as imaged in digital chest radiographs, as an objective mean to detect emphysema in patients with Chronic Obstructive Pulmonary Disease (COPD). A feature vector was extracted from the lung silhouette in lateral chest radiographs. The computation was based on the curvature of the lung border which was partitioned into three segments: for each of them the bending energy was obtained. The angles at the points where the three segments join were also measured. To test the validity of these descriptors, we applied multilayer neural networks to a data set of 180 lateral chest radiographs of which 70 from normal subjects and 110 from COPD patients with (n=56) and without emphysema (n=54). The procedure differentiated normal controls from COPDs with a sensitivity of 89.6%, and a specificity of 85.2%. Sensitivity and specificity in differentiating emphysematous from non emphysematous patients were 90.0%, and 83.6%, respectively.

Introduction

The development of Computer Aided Diagnosis (CAD) systems in chest imaging has opened new perspectives for the quantitative analysis of chest radiographs [1]. Digital chest radiography features higher spatial and density resolution as compared to conventional chest roentgenology [1].

In this report, we aimed at developing a computational descriptor of the shape of the lung silhouette in a sample of individuals including subjects with normal lung function tests and patients with established COPD. The latter group was further subdivided into two subgroups depending on the presence or absence of radiologic emphysema. The diagnosing or exclusion of emphysema was based on criteria which were validated in a pathologic-radiologic correlation study [2]. They include depression and flattening of the diaphragms and irregular radiolucencies of the lung fields as evaluated on the postero-anterior view; increased retrosternal space and flattening or concavity of the diaphragmatic contours as assessed on the lateral view. Emphysema is diagnosed when any two of the above criteria are present. Widening of the retrosternal space and flattening of the diaphragmatic contours are related to hyperinflation and may alter the shape of the lung silhouette. Our aim was to provide a quantitative description of such alterations.

Here, we describe the computation of morphological features of the lung fields as imaged in digital lateral chest radiographs where both hemidiaphragms and retrosternal space are visualized. Evaluation of these features on a large patient dataset is reported. We used artificial neural networks to differentiate normal subjects from patients with COPD and, within the latter group, to discriminate the patients with emphysema from those without.

Computational features of lung shape

Flattening of the diaphragms, and increased retrosternal space are typical radiologic signs of emphysema related to hyperinflation. Figure 1 shows the radiographs of a) a normal subject, b) a patient with COPD and no evidence of emphysema c) a patient with COPD and emphysema. In the latter, the diaphragm contour has a reduced curvature and both the costophrenic and cardiophrenic angles are widened.

We introduced the following description of the lung silhouette in the lateral view which is based on the curvature of lung silhouette. Let \( x(s) = (x(s), y(s)) \) the parametric equation of the lung border, the parameter \( s \) being the curvilinear abscissa of the curve. The curvature \( k(s) \) identifies the given planar curve \( x(s) \) in a unique manner, independently of its position. In this regard, curvature provides a translation- and rotation-invariant description of the lung shape. This is a desirable property as it tends to counteract the effects of patient positioning during image acquisition.

As to computation of curvature, several approaches are reported [3]. In the following we utilized the equation:
\[ \kappa(s) = \frac{x'y'' - x''y'}{(x'^2 + y'^2)^{3/2}} \]  

(1)

where \((x', y')\) and \((x'', y'')\) are the first and second derivative of \((x, y)\), respectively. They were estimated through the convolution of \(\kappa(s)\) with the derivatives of a Gaussian kernel \(G_\sigma(s)\) with \(\sigma\) standard deviation, according to the equations:

\[
x' = G'_\sigma(s) \otimes x(s), \quad x'' = G''_\sigma(s) \otimes x(s) \quad (2)
\]

\[
y' = G'_\sigma(s) \otimes y(s), \quad y'' = G''_\sigma(s) \otimes y(s)
\]

The value of \(\sigma\) was selected by experiment and set to 2 pixel units. Such a value ensured adequate regularization of differential operators without undesired smoothing effects.

In Figure 2 a typical plot of \(\kappa(s)\) is drawn. The peaks due to the apex \((A)\) of the lung and the diaphragmatic borders \((D_a, D_p)\) are marked.

From the mathematical standpoint, the curvature function \(\kappa(s)\) provides a complete description of the shape features of interest. However, it is redundant with respect to our aim. We therefore introduced a more compact representation (see Figure 3). First of all, we segmented the silhouette into three sections \(s_i, i = 1, 2, 3\) by locating the three points \(A\) (apex), \(D_a\) (anterior cardiophrenic angle), and \(D_p\) (costophrenic angle) which are obtained by finding the local maxima of \(\kappa(s)\). To describe the shape of each section we computed its bending energy:

\[
e_i = \int_{s_i} \kappa^2(s) \, ds \quad i = 1, 2, 3 \quad (3)
\]

It is a measure of curve deflection and has often been used to model biological shapes (see for example [4]). In addition, the three angles \(\alpha_i\) in the point where \(s_i\) join were also estimated (see Figure 3). The angles \(\alpha_i\) are often markedly widened in the images from diseased patients.
Experiments were performed using a dataset $S$ of lateral chest radiographs that were acquired by means of an IMIX Thorax 2000 digital system. It provides DICOM images with a $2000 \times 2000$ matrix (corresponding to a pixel size of 200 $\mu$m) and 12 bit of density resolution. The overall dataset $S$ included 180 radiographs: 70 from normal subjects (set $S_{\text{normal}}$) and 110 from COPD patients (set $S_{\text{disease}}$) with and without emphysema. Images from pathological subjects were analyzed by two independent experienced physicians who rated the presence or absence of emphysema according to Pratt’s criteria [2]. Fifty-four were categorized as COPD without emphysema (set $S_{\text{copd}}$), and 56 as COPD with emphysema (set $S_{\text{emphysema}}$). In all cases examined, the lung silhouette was traced by an experienced physician.

In the first experiment, we built the training-set $S_{\text{train}}$ by randomly selecting 40 images from $S_{\text{normal}}$ and 50 images from $S_{\text{disease}}$, respectively. The $S_{\text{train}}$ set was used to train the network, while the remaining image set $S_{\text{test}}$ was utilized to test its performance. Similarly, in the second experiment a set including 30 images from $S_{\text{copd}}$ along with 30 images from $S_{\text{emphysema}}$ were used as training-set. The remaining images served as validation set.

In both experiments, we performed 10 different randomized selections of the training- and test-set, and, for each selection, we trained the involved neural network and tested its performance. In this way, after training we obtained a set of 10 different networks. The results given in next section are the average values computed from such a network set.

As to the number of hidden units of the neural network, we tested different network architectures by varying the units per hidden layer. The best generalization capabilities were observed with 4 units per layer in the case of experiment $E_1$ and with 6 units per layer for experiment $E_2$.

To summarize, the feature vector:

$$ f = (e_1, e_2, e_3, \alpha_1, \alpha_2, \alpha_3) $$

was adopted as a descriptor of the lung shape and used in all our experiments.

Analysis of lung shape by artificial neural networks

To test the validity of the proposed lung-shape descriptor we performed two different classification tasks: $E_1$ differentiation of normals from COPDs, and $E_2$ detection of emphysema in COPD patients (see next section). To this end, artificial neural networks of the feed-forward type were employed. All the network units have a sigmoidal activation function (output range: $[0, 1]$). The network topology includes 6 input units that are fed by the components of the feature vector $f$, and two output units each representing the probability that the input pattern belongs to one of the two considered classes (i.e. normal/COPD , and emphysema/no-emphysema, respectively). In particular, the output units code the class according to a 1-of-2 scheme [5]. Let $\{o_i, i = 1, 2\}$ be the output values, the input vector is assigned to class $k$ given by:

$$ k = \max_i \{o_i\} $$

The network architecture is completed by two hidden layers each having a number of units dependent on the experiment considered (see next section). Networks were trained by using the back-propagation rule to minimize the sum-of-squares error over the training-set. Adaptive learning rate and momentum term were adopted. Uniform random values in the range $[-0.01, 0.01]$ were used to initialize connections weights. The number of training epochs ranged from $7 \times 10^2$ to $20 \times 10^3$. In all cases, the training process was stopped when the sum-of-squares error measured on the test-set started to increase.

Results and discussion

Results of experiment $E_1$, i.e. discrimination of normal from COPDs are summarized in Tables 1 and 2. In Table 1 we give the classification results obtained when the data of the training-set are used as network input. The values confirm that the used networks were able to learn the classification task.
Values in Table 2 are obtained from the test-sets and indicate the generalization capabilities. In particular, the average sensitivity in detecting pathological cases is 89.6% (minimum value 81.7%, maximum value 95.0%), with average specificity 85.2% (minimum value 80.0%, maximum value 90.0%), and average accuracy 88.2% (minimum value 83.3%, maximum value 93.3%).

Similarly, in Tables 3 and 4 we give the results for experiment $E_2$ regarding the recognition of emphysema in COPD patients. Values in Table 3 refers to the training-sets and indicate a good convergence of the training phase. In Table 4 the values for the test-sets are shown. Average sensitivity in detecting emphysema is 90.0% (minimum value 80.8%, maximum value 96.1%) , with average specificity 83.6% (minimum value 79.2%, maximum value 91.7%) , and average accuracy of 86.9% (minimum value 80.0%, maximum value 94.0%).

<table>
<thead>
<tr>
<th>True Category</th>
<th>Normal</th>
<th>COPD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classified as</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Normal</td>
<td>96.8%</td>
<td>1.2%</td>
</tr>
<tr>
<td>COPD</td>
<td>3.2%</td>
<td>98.8%</td>
</tr>
</tbody>
</table>

Table 1: Results of $E_1$ experiment: average values from the training-sets.

<table>
<thead>
<tr>
<th>True Class</th>
<th>Normal</th>
<th>COPD</th>
<th>Emphysema</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classified as</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COPD</td>
<td>95.3%</td>
<td>0.9%</td>
<td></td>
</tr>
<tr>
<td>Emphysema</td>
<td>4.7%</td>
<td>99.1%</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Results of $E_1$ experiment: average values from the test-sets.

<table>
<thead>
<tr>
<th>True Class</th>
<th>COPD</th>
<th>Emphysema</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classified as</td>
<td></td>
<td></td>
</tr>
<tr>
<td>COPD</td>
<td>83.6%</td>
<td>10.0%</td>
</tr>
<tr>
<td>Emphysema</td>
<td>16.4%</td>
<td>90.0%</td>
</tr>
</tbody>
</table>

Table 3: Results of $E_2$ experiment: average values from the training-sets.

<table>
<thead>
<tr>
<th>True Class</th>
<th>COPD</th>
<th>Emphysema</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
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Table 4: Results of $E_2$ experiment: average values from the test-sets.

Our results suggest that computer-aided quantitative analysis of chest radiographs is a useful tool in describing alterations in lung shape that occur in patients with emphysema. In the present study, the analysis was limited to the lateral chest radiograph, but we expect that the use of the postero-anterior view may further improve the rate of correct classification.

References


