Computer-aided diagnosis in chest radiography for detection of childhood pneumonia

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\textbf{Abstract}

Objectives: This article presents a novel approach based on computer-aided diagnostic (CAD) scheme and wavelet transforms to aid pneumonia diagnosis in children, using chest radiograph images. The prototype system, named Pneumo-CAD, was designed to classify images into presence (PP) or absence of pneumonia (PA).

Materials and methods: The knowledge database for the Pneumo-CAD comprised chest images confirmed as PP or PA by two radiologists trained to interpret chest radiographs according to the WHO guidelines for the diagnosis of pneumonia in children. The performance of the Pneumo-CAD was evaluated by a subset of images randomly selected from the knowledge database. The retrieval of similar images was made by feature extraction using wavelets transform coefficients of the image. The energy of the wavelet coefficients was used to compose the feature vector in order to support the computational classification of images as PP or PA. Methodology I worked with a rank-weighted 15-nearest-neighbour scheme, while methodology II employed a distance-dependent weighting for image classification. The performance of the prototype system was assessed by the ROC curve.

Results: Overall, the Pneumo-CAD using the Haar wavelet presented the best accuracy in discriminating PP from PA for both, methodology I (AUC = 0.97) and methodology II (AUC = 0.94), reaching sensitivity of 100% and specificity of 80% and 90%, respectively.

Conclusion: Pneumo-CAD could represent a complementary tool to screen children with clinical suspicion of pneumonia, and so to contribute to gather information on the burden of pneumonia estimates in order to help guide health policies toward preventive interventions.

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1. Introduction

Pneumonia is a relevant cause of children’s morbidity and mortality, and approximately two million children die from pneumonia every year, especially in developing countries [1].

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upon radiological findings. In public health, radiologically defined pneumonia has been used to estimate the vaccine preventable fraction of pneumonia and also to estimate the burden of pneumonia at the population level. Alveolar consolidation of a portion of the whole pulmonary lobule, or of the entire lung, and pleural effusion has been largely assumed as outcomes compatible with pneumonia of bacterial etiology in vaccine evaluation studies [3–5]. In such studies digital cameras are used to capture chest radiograph images and readers are trained for interpretation of chest radiographs for the diagnosis of pneumonia in children in accordance to the World Health Organization (WHO) guidelines [6,7]. In this way, it is of paramount importance to be able to discriminate between presence of lung shadows compatible with bacterial pneumonia and absence of such lesions, and agreement of readers not familiarized with the WHO guidelines is far from satisfactory in this area of X-ray diagnostics [8]. The low reproducibility of the image interpretation in the clinical routine opens room for the development of computational systems to assist pediatricians in the diagnosis of pneumonia and to standardize the reading of chest radiographic images.

Computer-aided diagnosis (CAD) systems have been proposed in an attempt to improve the performance of the diagnosis in the medical practice to minimize errors in image interpretation [9–13]. The contribution of the present work is the development of a prototype CAD system herein called Pneumo-CAD, capable of discriminating chest radiological patterns between pneumonia of bacterial etiology (PP) from absence of pneumonia (PA) in a population of patients previously evaluated by the attendant pediatrician. The ultimate purpose of the Pneumo-CAD is to suggest a diagnosis and to monitor the occurrence of pneumonia cases, to support public health preventive interventions. This approach uses wavelet transforms to extract lung image features and the weighted nearest-neighbour based on Euclidian metric to measure the similarity between images [14]. In the last decade wavelet transforms have been widely used to extract features of medical images. Applications of wavelets in the analysis of medical images have been based on the decomposition of a signal in multiresolution theory [15–19]. Progresses in the wavelets’ theory applied to the image diagnosis have produced outstanding promising alternatives that carry important advantages as wavelets cover all domain frequencies, allowing the construction of efficient systems.

The outline of this paper is as follows. Section 2 describes the data used to build up the knowledge database, the prototype Pneumo-CAD system and also the methodologies applied to classify a new image into PP or PA, relying on the wavelets theory. The experimental results are presented in Section 3. The discussion and conclusions are placed in Section 4.

2. Materials and methods

2.1. Study population and chest radiographic images

In July 1999, the vaccination against Haemophilus influenzae b (Hib) was introduced in the immunization program in Brazil. In May 2000, a population surveillance study was implemented in the municipality of Goiânia (1,090,581 inhabitants), Central Brazil, to evaluate the impact of the Hib vaccination in reducing the community-acquired pneumonia in children admitted to hospitalization. The surveillance network comprised 22 pediatric hospitals of the municipality. Details of this surveillance were presented elsewhere [20]. Briefly, at the health service units, children under-five years old with clinical suspicion of pneumonia were referred to chest radiograph and those with X-ray diagnosed by the pediatricians as pneumonia compatible with bacterial etiology were referred to hospitalization. Therefore this first pediatric screening was taken as a high pretest probability of pneumonia. At the hospital admission, the radiograph were photographed with digital camera Sony Mavica MVC-FD90 that captured the chest X-rays images at a resolution of 1024 × 768 pixels, with 8-bit gray scale, according to the WHO guidelines [5,7,21]. The chest radiographs were properly positioned on standard lightboxes that held two fluorescent light tubes of 15 W each. The pictures were taken in each of the hospitals, with the digital camera without flash. Fig. 1 shows two typical digital images of potential cases of pneumonia. It should be mentioned that the child is seen from the front, so the left lung (with the heart) appears on the right in the pictures, and vice versa.

2.2. CAD prototype system

As a result of the pneumonia surveillance study, a total of 1000 X-ray images (1024 × 768) pixels suspected of pneumonia by the pediatrician were concurrently read and interpreted for the presence of pneumonia by two independent radiologists especially trained to apply the WHO guidelines. Pneumonia
Diagnosis was confirmed by the readers in 74% of X-ray images (pretest prevalence), while normal chest radiograph or other diagnoses were confirmed in 22% and 4%, respectively. For the purpose of this study, we assumed as gold standard the reading as PP and PA provided by the two independent radiologists. To build up the knowledge database of the prototype Pneumo-CAD system a subset of 40 chest radiograph images (20 PP and 20 PA) were sequentially retrieved from the radiographic database, as described in Fig. 2.

A second subset of 20 images (10 PP and 10 PA), were randomly selected from the radiographic database as a test set, to evaluate the performance of the image classification of the Pneumo-CAD system. Thus, Pneumo-CAD prototype system comprised two consecutive modules. The first one corresponded to the construction of a knowledge database and in the second one the new image was classified based on the similarity of the image retrieved from the knowledge database (Fig. 2).

In general, the images \( F(x, y) \) can be indexed by its proper visual content, such as color, texture and geometric features. In the last decade, content-based image retrieval (CBIR) has appeared as a promising alternative in CAD construction [17,22]. The main advantage of CBIR is the ability to perform searches based on image visual content [23]. However, the current challenge has been the development of CBIR methods with high accuracy at low retrieval time [22,24]. For pneumonia radiological diagnosis, texture is considered the most important feature. Therefore, in this study we used texture as a visual feature, as texture plays a very important role in computer vision and pattern recognition, especially in the description of image content. Currently, texture features used in CBIR are mainly derived from discrete wavelet transform [25,26] and from Gabor filters [27]. Methods based on wavelet transforms provide better information on spatial location of the image with domain transformations and dimensionality reduction [28]. Gabor filters need computational power and require more memory storage for the features [27]. The texture features extracted by wavelets can be stored in a vector form, building a numeric representation of the image. The relevant information contained in the image is synthesized and can be stored on a knowledge database. In this work, two methodologies were developed, using the energy of wavelet transform coefficients, to build up the feature vector in order to classify images of chest X-ray into PP or PA.

For notation purpose, in the next sections matrices are represented by bold capital letters, vectors by bold lowercase letters, and scalars by italic characters. Elements of a sequence or vector are denoted by italic characters with a subscript index. The mathematics symbols and quantities used in the next sections are defined in Table 1.

2.3. Fast wavelet transform

Fast wavelet transform (FWT) can be calculated in a fast manner by using a filter bank structure [18,29,30] of the form, depicted in Fig. 3. 2-D scaling \( \psi(x, y) \) and wavelet functions \( \psi^H(x, y), \psi^V(x, y), \psi^D(x, y) \) can be expressed as linear combination of double-resolution copies of themselves [31]:

\[
\psi(x) = \sum_n h_n(n) \sqrt{2} \psi(2x - n) \tag{1}
\]
Table 1 – Mathematics symbols

<table>
<thead>
<tr>
<th>Symbols</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$*$</td>
<td>Convolution operation</td>
</tr>
<tr>
<td>$j$</td>
<td>Scale</td>
</tr>
<tr>
<td>$n$</td>
<td>Horizontal translation</td>
</tr>
<tr>
<td>$m$</td>
<td>Vertical translation</td>
</tr>
<tr>
<td>$i$</td>
<td>$H, V, D$; horizontal, vertical, diagonal wavelet functions</td>
</tr>
<tr>
<td>$x$</td>
<td>Columns of vector or matrix</td>
</tr>
<tr>
<td>$h$</td>
<td>Vector dimension</td>
</tr>
<tr>
<td>$e$</td>
<td>Coefficients’ energy</td>
</tr>
<tr>
<td>$\psi_{H,V,D}(x, y)$ or $\psi(x, y)$, $i = H, V, D$</td>
<td>2-D wavelet functions</td>
</tr>
<tr>
<td>$W_i(j + 1, m, n)$</td>
<td>Input for the first iteration of the filter bank. In this work, the image being transformed. In our case, $F(x, y) = W_i(j + 1, m, n)$. The horizontal, vertical, and diagonal coefficients at level three are generated from the input $W_i(j + 1, m, n)$ used to calculate the coefficients’ energy. Therefore, the image is represented by their coefficients. The notion of image, pixels with light intensities and their anatomical coordinate is represented by their approximation coefficients $W_i(j + 1, m, n)$ and vertical, horizontal, and diagonal detail coefficients $W_i(j, m, n)$.</td>
</tr>
<tr>
<td>$P(x, y)$</td>
<td>2-D scaling function</td>
</tr>
<tr>
<td>$p(x)$</td>
<td>1-D scaling function</td>
</tr>
<tr>
<td>$\psi(x)$</td>
<td>1-D scaling function</td>
</tr>
<tr>
<td>$\psi_j$</td>
<td>Represent down-sampling operation</td>
</tr>
<tr>
<td>$\psi_{1/2}$</td>
<td>Low-pass filter</td>
</tr>
<tr>
<td>$h_i$</td>
<td>High-pass filter</td>
</tr>
<tr>
<td>$W_i(j + 1, m, n)$</td>
<td>Discrete approximation wavelet coefficients of the input image at scale $j$</td>
</tr>
<tr>
<td>$w_i(j, m, n)$</td>
<td>Discrete details wavelet coefficients of the input image at scale $j$. In this work, only discrete wavelet transform is used</td>
</tr>
<tr>
<td>$w_i(x)$</td>
<td>Approximation coefficients of the input image at scale $j$</td>
</tr>
<tr>
<td>$w_i^j$</td>
<td>Horizontal detail coefficients at scale $j$</td>
</tr>
<tr>
<td>$w_i^j$</td>
<td>Vertical detail coefficients at scale $j$</td>
</tr>
<tr>
<td>$w_i^j$</td>
<td>Diagonal detail coefficients at scale $j$</td>
</tr>
<tr>
<td>$\rho_{w_i^j}$</td>
<td>Probability of occurrence of the discrete wavelet coefficient $w_i^j$. $i = H, V, D$</td>
</tr>
<tr>
<td>$pqr$</td>
<td>Vector concatenation operation</td>
</tr>
<tr>
<td>$p$</td>
<td>Energy vectors to the wavelet coefficients $w_i^j$. $i = H, V, D$ at the first filter bank iteration. $p = [x_1, x_2, \ldots, x_n]$</td>
</tr>
<tr>
<td>$q$</td>
<td>Energy vectors to the wavelet coefficients $w_i^j$. $i = H, V, D$ at the second filter bank iteration. $q = [x_1, x_2, \ldots, x_n]$</td>
</tr>
<tr>
<td>$r$</td>
<td>Energy vectors to the wavelet coefficients $w_i^j$. $i = H, V, D$ at the third filter bank iteration. $r = [x_1, x_2, \ldots, x_n]$</td>
</tr>
<tr>
<td>$x = [pqr]$</td>
<td>Feature vector for the left side of the lung</td>
</tr>
<tr>
<td>$t$</td>
<td>Energy vectors to the wavelet coefficients $w_i^j$. $i = H, V, D$ at the first filter bank iteration. $t = [x_1, x_2, \ldots, x_n]$</td>
</tr>
<tr>
<td>$u$</td>
<td>Energy vectors to the wavelet coefficients $w_i^j$. $i = H, V, D$ at the second filter bank iteration. $u = [x_1, x_2, \ldots, x_n]$</td>
</tr>
<tr>
<td>$v$</td>
<td>Energy vectors to the wavelet coefficients $w_i^j$. $i = H, V, D$ at the third filter bank iteration. $v = [x_1, x_2, \ldots, x_n]$</td>
</tr>
<tr>
<td>$y = [tuv]$</td>
<td>Feature vector for the right side of the lung</td>
</tr>
<tr>
<td>$e$</td>
<td>Two side of the lung merged into a single feature vector</td>
</tr>
<tr>
<td>$w$</td>
<td>Weight giving by the left side of the lung. $w$ can assume values in an interval $[0, 1]$</td>
</tr>
<tr>
<td>$1 - w$</td>
<td>Weight giving by the right side of the lung</td>
</tr>
<tr>
<td>$d$</td>
<td>Euclidian distance between feature vectors or L2 metric</td>
</tr>
<tr>
<td>$S.D.$</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>$\omega$</td>
<td>Probability of the image to be normal or compatible with radiological pneumonia pattern</td>
</tr>
<tr>
<td>$\omega$</td>
<td>Weights assigned to the 15 most similar of the 40 images of the knowledge database</td>
</tr>
<tr>
<td>$\text{diag}$</td>
<td>Dichotomous variable. Assume values 0 for pneumonia or 1 for normal diagnostic</td>
</tr>
<tr>
<td>$\omega_i$</td>
<td>Images which has the smallest Euclidian distance</td>
</tr>
<tr>
<td>$d_i$</td>
<td>Distance of prototype Pneumo-CAD search</td>
</tr>
<tr>
<td>$\omega_{p}$</td>
<td>Probability of obtaining a result at least as extreme as a given data point, assuming the data point was the result of chance alone</td>
</tr>
<tr>
<td>$\omega$</td>
<td>Sum of the residuals</td>
</tr>
</tbody>
</table>

\[
\psi(x) = \sum_{n} h_x(n) \sqrt{2} \psi(2x - n)
\]

where, $h_x$ and $h_y$ are the filter coefficients of FWT.
filters, respectively. Blocks containing a ↓ 2 represent down-sampling, extracting every other point from a sequence of points. The series of filtering and down-sampling operations used to compute \( w^i_j(n, m, n) \) is, for example
\[
\begin{align*}
\phi_j(n, m, n) = h_1(-m) \cdot [h_1(-n) \cdot w^i_j(n, m, n)]_{m=2k,k \geq 0} \\
&\quad \text{for } i = \{H, V, D\}
\end{align*}
\]
where * denotes convolution.

Evaluating convolutions at nonnegative, even indices is equivalent to filtering and down-sampling by 2 \([29]\). When an X-ray image \( f(x, y) \) is the high resolution for the image being transformed, it serves as the \( w^i_j(n+1, m, n) \) input for the first iteration. The operations in Fig. 3, use neither wavelets nor scaling functions, only their associated wavelet and scaling vectors.

In the CBIR context, it is attempted to extract texture features in any part of the image that represents homogeneous regions (e.g. alveolar consolidation) in several resolution of the filter bank (Fig. 3). The main idea is to find relevant homogeneous regions using the energy of wavelet transform coefficients at different iterations.

Initially, a pilot study was conducted to evaluate the level of iteration that better represented the chest radiograph features. We found that image decomposition at the third iteration level presented the best feature representation, neither discarding useful nor retaining superfluous information. In this investigation, the energy feature of the image used to build up the feature vector was extracted from the energy of the wavelet transform coefficients using eight types of wavelets: Haar, Daubechies family (Db 2, Db 4, and Db 8), Coiflets family (Coif 2 and Coif 4) and Biorthogonal family (Bior 2.2 and Bior 4.4).

2.4. Vector generation

Several parameters have been used in the CBIR context to retrieve image, including entropy, energy and standard deviation \([24,32,33]\). We opted to use the energy of detail wavelet transform coefficients at the third iteration level for texture feature representation \([24,27,28,34]\).

Fig. 4 shows the mean values of the energy of the feature vectors yielded by the wavelet transforms by applying Eq. (4). Notice that the Haar wavelet produced higher values of energy, peaked at the 3, 6 and 9 positions. This emphasizes the potential of the Haar wavelet in dealing with texture data, since textures are associated with high energy values.

The feature vector for the left side \( (x) \) and the right side \( (y) \) of the lung was created and the coefficients’ energy was obtained by:
\[
\varepsilon = \sum [\rho(w^i_j)]^2.
\]
where \( \rho(w^i_j) \) represents the probability of occurrence of the wavelet transform coefficient \( w^i_j, i = H, V, D \) in the transformed image \([35]\).

The coefficients at the first \( (p) \), second \( (q) \), and third \( (r) \) iteration level from the left side of the lung and the energy of the vectors \( p, q, \) and \( r \) were obtained and stored in the first, second and third indexes, for the features vector of the left side \( x \). In analogy, the coefficients at the first \( (t) \), second \( (u) \), and third \( (v) \), iteration level from the right side of the lung \( (t, u, v) \) were obtained and stored in the first, second and third indexes in the features vector of the right side \( y \). Thus, the procedure for developing the feature vector of the left lung was \( x = [p|q|r] \) and for the right lung was \( y = [t|u|v] \).

The feature vectors obtained for each side of the lung in the same image were merged into a single feature vector using the equation:
\[
e = (x \cdot w) + (y \cdot (1 - w))
\]
where \( w \) and \( (1 - w) \) are the weights given to the left and the right side of the lung. The variable \( w \) can assume values in an interval of \([0,1]\). We chose to test weighted values of 0.40, 0.50 and 0.60 to compute \( e \), since the two sides of the lung may not hold the same amount of discriminatory information.

The similarity between the image under investigation and the images stored on a knowledge database was measured by the Euclidian distance or L2 metric \([14,36]\). This metric associates the feature vector to FP or PA diagnosis. The Euclidian
Fig. 5 – Plot of the median distance between pairs of types PA:PP, PA:PA and PP:PP images. PP = pneumonia; PA = normal.

The distance between feature vectors is defined by:

\[
d = \sqrt{\sum_{i=1}^{9} (e' - e)^2}
\]

where \(e'\) is the vector for the image to be classified.

Fig. 5 displays the mean distance between the pairs of PP and PA images. The pair PP:PP presented a statistically lower mean distance (0.22; S.D. = 0.20) when comparing to PA:PA (0.30; S.D. = 0.12) and PA:PP (0.50; S.D. = 0.12) type pairs. This lower mean distance between pair PP:PP is due to the size of the alveolar consolidation of a portion of the whole pulmonary lobes or of the entire lung, as well as the anatomical localization in the different lobes.

To test the performance of the prototype Pneumo-CAD system in classifying the chest radiograph into PP and PA two methodologies were developed, both of them based on nearest-neighbour (NN) classification schemes.

3. Experiments

3.1. Methodology I

The rationale of this methodology was to find out in the knowledge database a rank-weighted NN of the new image to be classified. Several experiments were performed to determine the number of images to be selected in a knowledge database to compute the classification result. The aim of this experiment was to find out the number of images that maximized the classification accuracy. The best accuracy was obtained selecting the 15 most similar (least distant) of the 40 images of the knowledge base according to the equation:

\[
\delta = \sum_{i=1}^{15} (\omega_i \cdot \text{diag}_i)
\]

where \(\delta\) measures the probability of the image to be normal or compatible with radiological pneumonia pattern. The variable \(\delta\) ranges from [0,1], which indicates that the closer \(\delta\) is to 0, the greater the probability of being pneumonia, while the closer to 1, the greater the probability of being a normal image. The dichotomous variable diag assumes values 0 for pneumonia or 1 for normal diagnostic according to the diagnosis provided by the two radiologists for the 40 images selected from the knowledge database. The variables \(\omega_i\) are weights assigned to the 15 most similar of the 40 images of the knowledge database.

To illustrate how this methodology works, we selected one chest radiograph from the clinical routine and simulated the process of classification in Table 2 assuming \(\delta < 0.65\) to discriminate pneumonia from normal images. The \(d_1\) is the image which has the smallest Euclidian distance in relation to the analyzed image; \(d_2\) is the image with the second smallest distance and so on. The first retrieved image \(d_1\) from the knowledge database is weighted as 0.20 on the image classification, the second image \(d_2\) is weighted as 0.15, the third image is weighted as 0.12 and so on until the 15th index. The sum of the weights \(\omega\) is 1.0. By applying Eq. (7) we found \(\delta = 0.62\), which is lower than the value 0.65, set up as the cut-off point for classifying the image as pneumonia. Therefore, in this simulated example the new image would be classified as pneumonia. Results provided by this methodology employing different wavelet transforms are shown in Section 4.

### 3.2. Methodology II

In this methodology there is no fixed number of images to ascertain the \(\delta\) value. Thus, \(\delta\) is distance-dependent weighting

<table>
<thead>
<tr>
<th>(d_i)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\omega_i)</td>
<td>0.20</td>
<td>0.15</td>
<td>0.12</td>
<td>0.11</td>
<td>0.09</td>
<td>0.08</td>
<td>0.06</td>
<td>0.05</td>
<td>0.04</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>diag</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>(\omega_i \cdot \text{diag}_i)</td>
<td>0.20</td>
<td>0.15</td>
<td>0.12</td>
<td>0.09</td>
<td>0.08</td>
<td>0.06</td>
<td>0.05</td>
<td>0.04</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>(\sum_{i=1}^{15} (\omega_i \cdot \text{diag}_i))</td>
<td>0.20 + 0.15 + 0.12 + 0 + 0 + 0.09 + 0.08 + 0.06 + 0.05 + 0 + 0 + 0.02 + 0.02 + 0.01 + 0.01 = 0.62</td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>Classification outcome</td>
<td>(\delta = 0.62 &lt; 0.65) (cut point) → image classified as pneumonia</td>
<td></td>
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</tbody>
</table>

\(d_i\): images ranked-15 least distance; \(\omega_i\): respective weights assigned to each of the 15 most similar of the images of the knowledge database; diag: image of the knowledge database (gold standard) diagnosed as pneumonia (0) or normal (1); \(\delta\): probability of the image being pneumonia or normal.
NN for classifying the image, defined by Eqs. (8)–(10). The radius of prototype Pneumo-CAD search (rps) for the classification process is defined interactively by the Pneumo-CAD system user. Thus, all images from the test set with Euclidian distance smaller than the rps will compose the set of images used for the classification of the tested image. The classification process uses the set of images defined by f to store the differences between rps and the vector e. In Eq. (8) the weight declines linearly with the Euclidian distance until its becomes zero at and beyond the chosen rps. The vector f stores in an ordered way all the distances between the image which is being classified and the n other images of the knowledge database

\[ f_i = rps - e_i \] (8)

The value v is the sum of the residuals (0.50–0.05 = 0.45, 0.50–0.09 = 0.41, 0.50–0.35 = 0.15, 0.50–0.36 = 0.14) of f as showed in Table 3.

\[ \delta = \sum_{i=1}^{k} f_i \] (9)

\[ \delta = \frac{1}{v} \sum_{i=1}^{k} f_i \cdot diag_i \] (10)

where diag, is the images’ outcome (1 – normal; 0 – pneumonia) and \( \delta \) is a value from 0 to 1 as defined by methodology I. To test methodology II several rps ranging from (0.15, 0.20, . . . , 0.55) were chosen to establish the cut-off point that maximized the image classification accuracy. Table 3 simulates the process of classifying a given image, in which \( \delta \) is calculated for rps equal to 0.50 and holds the same 0.65 cut-off point for classifying the image as pneumonia or normal. In this example, the distance \( f_i \) of a given image to be classified is calculated by subtracting the ei from the value 0.50 of the rps. Thus, for the first image \( d_1 \) the corresponding \( f_1 \) is 0.45 (0.50–0.05), for the image \( d_2 \) the corresponding \( f_2 \) is 0.41 (0.50–0.09) and so on. In this simulation the new image presented \( \delta \) equal to 0.90, which is higher than the established cut-off point of 0.65; therefore the image would be classified as normal by this methodology.

### 3.3. Data analysis

The accuracy of methodologies I and II was assessed by the receiver operating characteristic (ROC) curve [37–39]. The area under the ROC curve (AUC) was used as a summary to identify the best wavelet transform that discriminated presence from absence of a pneumonia image [37]. The ROC curve is a graphic plot of the values of sensitivity (Y axis) versus 1-specificity (X axis) for a binary classifier system, in which the values can vary as a function of different delta scores (cut-off). In this study the obtained delta scores of the test set

### Table 3 – Computation process of image classification by methodology II

<table>
<thead>
<tr>
<th>Wavelets</th>
<th>Methodology I</th>
<th>Methodology II</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AUC</td>
<td>95% CI</td>
</tr>
<tr>
<td>Haar</td>
<td>0.97</td>
<td>0.91–1.00</td>
</tr>
<tr>
<td>Daubechies 2</td>
<td>0.76</td>
<td>0.54–0.98</td>
</tr>
<tr>
<td>Daubechies 4</td>
<td>0.70</td>
<td>0.46–0.94</td>
</tr>
<tr>
<td>Daubechies 8</td>
<td>0.64</td>
<td>0.37–0.91</td>
</tr>
<tr>
<td>Coiflets 2</td>
<td>0.69</td>
<td>0.44–0.95</td>
</tr>
<tr>
<td>Coiflets 4</td>
<td>0.69</td>
<td>0.44–0.95</td>
</tr>
<tr>
<td>Biortogonal 2.2</td>
<td>0.71</td>
<td>0.46–0.95</td>
</tr>
<tr>
<td>Biortogonal 4.4</td>
<td>0.72</td>
<td>0.47–0.96</td>
</tr>
</tbody>
</table>
was used as discrimination threshold. The ROC can also be represented equivalently by plotting the fraction of true positives (true positive rate) versus the fraction of false positives (false positive rate). MedCalc® Software (ver. 9.0.1.1) was used to calculate the AUC with the corresponding 95% confidence interval (95% CI) and also to conduct the pairwise comparison of the ROC curves for the two NN methodologies. The AUC with 95% CI that excluded 0.5 were considered significant results. The statistical significant differences were set as \( p \) values <5%.

4. Results

Overall, the best performance of the Pneumo-CAD for the two methodologies was achieved when using wavelets weighted at 0.60 (r) and 0.40 (l), which is similar to use 60% of the right feature vector energy and 40% of the left feature vector energy to compose the final image classification. The use of different weights for each lung side added 12% in the AUC; nevertheless, this addition was not statistically significant (data not shown). Table 4 summarizes the performance of methodologies I and II for the eight wavelet transforms weighted at 0.60 (r) and 0.40 (l). Among all the wavelets we found that the Haar wavelet presented the best accuracy in discriminating PP from PA images, yielding the largest area under the ROC curve either for methodology I (0.97) or for methodology II (0.94). Comparison between the ROC curve of both methodologies (Fig. 6) found that the AUC did not differ statistically (\( p = 0.618 \)). For methodology I the Pneumo-CAD prototype system identified correctly all the pneumonia images of the test set reaching a true-positive rate of 100% while 2 normal images were misclassified as pneumonia leading to a 20% false positive rate; the corresponding values for methodology II were 100% and 10%. The best combination of sensitivity and specificity for methodology I and II was obtained with \( \delta \) of 0.10 and 0.35, respectively. The higher AUC (0.94) achieved by methodology II was obtained for a radius of the Pneumo-CAD search of 0.40 from which the AUC remained constant (Fig. 7). Thus, confronting the results of both methodologies, we found that methodology I, which used the fifteen most similar images out of the 40 images in the knowledge database, proved to be more capable of correctly classifying chest radiographs with suspicious diagnosis of pneumonia.

5. Discussion

There is a paucity of studies that used CAD in infants. To the best of our knowledge no study has been proposed based on CAD to aid pneumonia diagnosis in children so far. In this paper we tested several wavelet schemes for the prototype creation and two weighted nearest neighbour-prototypes schemes for classifying chest radiographs into pneumonia and absence of pneumonia. The wavelet transform coefficients proved to be a useful tool in the process of chest radiographies classification in both tested methodologies. The best results were obtained when considering separately and averaging the resulting feature vectors at 0.60 versus 0.40, respectively, for the right and left lung side.

The prototype Pneumo-CAD presented good discriminatory power to classify chest radiographs in PP or PA, which could contribute to minimize interpretation errors and also produce comparable results when applied to different epidemiologic studies of childhood pneumonia. The prototype proposed could assist pneumonia control program in the screening of children with clinical suspicion of pneumonia. Pneumo-CAD system was conceived to be applied in the pediatric patients previously clinically screened, for instance in a posttest probability scenario. It is worthwhile reminding that this prototype was tested in a situation of high pretest prevalence (74%) since all images had been
Summary points

What was known before the study – state of the art:

- The inter-observer agreement in the interpretation of chest radiograph images for pneumonia presents low reproducibility.
- CAD has been proposed in medical practice to standardize the reading of chest radiograph images.
- At present, the wavelet transform is used mainly with two different purposes: multiresolution orthogonal signal decomposition and image analysis.

What the study has added to the body of knowledge – new contributions:

- Eight types of wavelets were tested to develop a prototype computer-aided pneumonia diagnostic scheme (Pneumo-CAD) to classify pediatric chest radiograph images into presence or absence of pneumonia.
- Pneumo-CAD prototype with the Haar wavelet transform yielded high accuracy in terms of Area under the ROC curve (up to 97%) in discriminating pneumonia from absence of pneumonia images.
- The development of a CAD based on wavelet transform could be a useful complementary tool for surveillance of childhood pneumonia.

previously screened by the attendant pediatricians. Thus, this prototype system is supposed to be usually applied in such a circumstance which will probably lead to a favorable balance between false positive and false negative results achieving high specificity, with low rate of false positive results.

Both methodologies herein developed can be used to perform automatic interpretation of chest pneumonia’s images, for screening purpose, considering their high sensitivity and specificity. The advantage of methodology II is the possibility of adjustment of the classification process as one can establishes a minimum standard to classify pneumonia-suspected images, according to the purpose of the Pneumo-CAD user. However, the higher accuracy of methodology I, besides its threshold of 0.10, makes this methodology an attractive tool, especially considering the threshold of 0.35 of methodology II.

Some limitations of this CAD prototype should be mentioned. We made no attempt to conduct a pre-processing image in order to minimize possible noises during the image classification process [40]. However, 85% of the chest X-rays images taken at the health services among the pediatric population and stored in our digital dataset have been considered of good quality by the radiologists [20]. Chest radiographs with the child not standing upright occur in exceptional occasions. Another point is that the feature vector of the Pneumo-CAD was constructed to distinguish well-defined lung shadows compatible with bacterial pneumonia which comprises alveolar consolidation images. Thus, to detect difference between infiltrations with fluffy and sharply delineated contour were not the purpose of the Pneumo-CAD. It would be desirable to conduct further experiments that evaluated the effect of having different PP:PA ratios in the knowledge base or different pneumonia prevalence levels in the test population.

The methodologies described in this paper can be used in a public health environment to evaluate the impact of the introduction of conjugate vaccines to reduce childhood pneumonia. Applying such computerized tools in different studies will standardize the interpretation of chest radiographs and so will increase the probability that any difference inter-studies reflects the real geographic differences of pneumonia epidemiology and differences in vaccination effectiveness. Among the available interventions against childhood pneumonia, vaccination is the most efficacious one. Lack of studies proving the cost-effectiveness of such interventions has hampered the vaccine introduction in the immunization program in Brazil. Pneumo-CAD system could represent a complementary tool in monitoring the burden of bacterial pneumonia at the pediatric population level to support the public health authorities in the decision of introducing the vaccination against pneumonia.

REFERENCES


