Automatic Pediatric Otitis Detection by Classification of Global Image Features

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- otoscopy remains the cornerstone in the diagnosis of otic (ear) diseases;
- the visual inspection of the eardrum is performed simply with an otoscope or video-otoscope;
- the interpretation of eardrum images is not straightforward; diagnostic aid may be useful in deploying unqualified personnel or telemedicine for remote areas.
- image processing may help in automatically detecting common ear diseases
Anatomic landmarks

- the handle of the malleus
- the reflection triangle
- the tympanic annulus
- the wall of the auditory canal
Typical cases: normal
Typical cases: otitis (1)
Typical cases: otitis (2)
The images are extracted as still frames from the video recorded during the otoscopy performed by a specialist; the images are 768 by 576 pixels; two sets of 100 images; same video-otoscope, different settings (due to slight modifications in time and operator change) almost equal parts of normal and pathologic ears (various types of otitis, other diseases, follow-ups,...)
The current approach investigates the performance and limits of color image description using:

- Color Histogram
- Color Coherence Vectors

Classification is made using:

- k-Nearest Neighbor
- Decision Trees
- Linear Discriminant Analysis
- Naïve Bayes
- Multi Layer Neural Networks
- Support Vector Machine
Color Descriptors - Color Histogram (1)

The histogram shows how many times a particular color intensity appears in an image.

<table>
<thead>
<tr>
<th>0</th>
<th>1</th>
<th>1</th>
<th>2</th>
<th>4</th>
</tr>
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<tbody>
<tr>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
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<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>1</td>
</tr>
</tbody>
</table>

Image

Histogram
Color Descriptors - Color Coherence Vectors (2)

- Based on the color histogram
- Each pixel is checked if it is located in a large one-color region or not.
- If so, the pixel is called coherent, otherwise incoherent
- Creates two histograms
  - one with coherent points
  - one with incoherent points

![Color Coherence Vectors Descriptor](chart.png)
Classifiers - k-Nearest Neighbor (1)

- For a given query point \( q \), assign the class of the nearest neighbour.

- Compute the \( k \) nearest neighbours and assign the class by majority vote.

\[
k = 1
\]

\[
k = 3
\]

Properties:
- Easy to understand and to code,
- Training is very fast,
- Sensitive to noise, irrelevant features,
- Classification is computationally expensive \( O(nd) \),
- Large memory requirements,
- More frequent classes dominate results.
- Decision Trees divide the feature space into parallel rectangles.
- Classification of an input vector is done by traversing the tree beginning with the root node, and ending with the leaf.
- Each node of the tree computes an inequality (ex. $x_2<3$, yes or no) based on a single input variable.
- Each leaf is assigned to a particular class.
Classifiers - Linear Discriminant Analysis (3)

• Find an optimal projection space along which the classes are best separated:
  • Maximizes the variance between different classes
  • Minimizes the variance of the individual classes
Classifiers - Naïve Bayes (4)

- A statistical classifier: performs probabilistic prediction using class membership probabilities
- Uses a simplified assumption: attributes are conditionally independent (no dependence relation between attributes):

\[ P(X | C_i) = \prod_{k=1}^{n} P(x_k | C_i) = P(x_1 | C_i) \times P(x_2 | C_i) \times \cdots \times P(x_n | C_i) \]

- This greatly reduces the computation cost: Only counts the class distribution (mean and variance)
- The conditional probabilities are usually computed based on Gaussian distribution with a mean \( \mu \) and standard deviation \( \sigma \)

\[ g(x, \mu, \sigma) = \frac{1}{\sqrt{2\pi \sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \]
Classifiers - Multi Layer Neural Networks (5)

- Information processing occurs at many simple elements called neurons;
- Signals are passed between neurons over connection links;
- Each connection link has an associated weight, which multiplies the signal transmitted in a typical neural net; each neuron applies an activation function (usually nonlinear) to its net input to determine its output signal.
Classifiers - Support Vector Machine (6)

General idea: the original input space can be mapped to a higher-dimensional feature space where the training set is linear separable.

- Defines an optimal hyperplane that maximize margins

\[ \vec{w} \cdot \vec{x} + b = -1 \]
\[ \vec{w} \cdot \vec{x} + b = 1 \]
\[ \vec{w} \cdot \vec{x} + b = 0 \]
## Implementation and Evaluation (1)

<table>
<thead>
<tr>
<th>Classification Algorithm</th>
<th>Color Descriptor</th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>Color Histogram HSV</td>
<td>Color Coherence Vectors</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Normal cases</td>
<td>Otitis cases</td>
<td>Mean</td>
<td>Normal cases</td>
</tr>
<tr>
<td>Without Classification</td>
<td>60.20</td>
<td>37.12</td>
<td>56.21</td>
<td>61.00</td>
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<tr>
<td>Nearest Neighbor</td>
<td>89.09</td>
<td>36.47</td>
<td>68.82</td>
<td>80.01</td>
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<td>Decision Trees</td>
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<td>0</td>
<td>59.13</td>
<td>23.63</td>
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<td>LDA</td>
<td>55.26</td>
<td>72.72</td>
<td>65.59</td>
<td>63.15</td>
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<tr>
<td>Naive Bayes</td>
<td>81.81</td>
<td>47.36</td>
<td>67.74</td>
<td>100</td>
</tr>
<tr>
<td>Neural Networks</td>
<td>83.63</td>
<td>47.36</td>
<td>68.82</td>
<td>78.18</td>
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<tr>
<td>SVM</td>
<td>85.45</td>
<td>34.21</td>
<td>64.51</td>
<td>89.09</td>
</tr>
</tbody>
</table>
Implementation and Evaluation (2)

- SVM and neural networks improve the system’s performance with the highest percentage, but they have the highest complexity during the training phase.
- Decision trees failed on classification tasks
- Naïve Bayes has medium performance for Color Histogram, and runs out for Color Coherence Vectors (it has recognized all the samples as normal cases).
- LDA has a little increase of performance and lower computational effort in classification phase.
- K-Nearest Neighbor performance is strongly conditioned by the number of selected neighborhood and it needs large memory requirements for medium efficiency.
Conclusions

Color alone does not provide a sufficient discriminative power for otitis identification.

The joint use of the tympanic color and auditory canal color is shown to significantly improve the performance.

Additional factors must be considered:
- the visual texture of the tympanic membrane,
- the contrast around the tympanic membrane,
- the presence/absence of the light reflection triangle,
- the presence/absence of any contours of air/liquid bubbles.