EXTRACTING MORPHOLOGICAL HIGH-LEVEL INTUITIVE FEATURES (HLIF) FOR ENHANCING SKIN LESION CLASSIFICATION

Robert Amelard, Alexander Wong, David A. Clausi
{ramelard, a28wong, dclusi}@uwaterloo.ca

Introduction

Melanoma causes the most deaths worldwide of all skin diseases [1]. One in five Americans is expected to develop melanoma in their lifetime [2]. If diagnosed in its infancy, a patient’s five-year survival rate is 98%. Otherwise the five-year survival rate falls to 62% if melanoma has spread to surrounding tissues, and a bleak 16% if the melanoma has spread to remote parts of the body [3]. The current clinical diagnostic standard is visual inspection. A widely-used metric is the “ABCD” rule [4]. Expert dermatologists using ABCD exhibit 76.0% - 87.7% sensitivity and 61.0% - 77.8% specificity with the aid of a dermoscope [5]. However, fewer than 48% of US fellows of the American Academy of Dermatology use dermoscopes [6].

Proposition: We show that a set of high-level intuitive features (HLIFs), used on standard camera images, can quantitatively describe the degree of irregularity about a lesion’s border.

“High-level Intuitive Feature”: a feature that has been carefully designed such that its formulation models a human-observable phenomenon.

Method & Results

HLIF for Fine Irregularities

Idea: capture “spiky” border irregularities.
Model: calculate the normalized change in area from morphological opening and closing.

\[ f_1^B = \frac{A_{closed} - A_{lesion}}{A_{lesion}} + \frac{A_{lesion} - A_{opened}}{A_{lesion}} \]

HLIF for Coarse Irregularities

Idea: capture general structural irregularities.
Model: compare the perimeters of the original lesion border with a coarse border representation using Fourier descriptors.

\[ f_2^B = \frac{|P_{lesion} - P_{low}|}{P_{lesion}} \]

HLIF for Average Malignant Comparison

Idea: capture the degree to which this lesion looks like a malignant lesion.
Model: compute the sum of squared difference between the magnitude of the “average” malignant lesion’s shape and a new lesion’s shape in the frequency domain.

\[ f_3^B = \sum_{u=0}^{N-1} |\tilde{C}(u)| - |\tilde{C}(u)|^2 \]

206 images

(www.dermis.net)

Illumination standardization [7], Rotation- and scale-invariance

Feature set Description # features Sensitivity Specificity Accuracy

<table>
<thead>
<tr>
<th>Feature set</th>
<th>Description</th>
<th># features</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>FC</td>
<td>Cavalcanti et al. feature set [7]</td>
<td>52</td>
<td>83.19%</td>
<td>74.71%</td>
<td>79.61%</td>
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<tr>
<td>FCM</td>
<td>Modified FC [8]</td>
<td>48</td>
<td>84.87%</td>
<td>75.86%</td>
<td>81.07%</td>
</tr>
<tr>
<td>FT</td>
<td>FCM ( \cup {f_i^B}_i )</td>
<td>51</td>
<td>90.76%</td>
<td>82.76%</td>
<td>87.38%</td>
</tr>
</tbody>
</table>

Conclusions

High-Level Intuitive Features (HLIFs) capture objective information about some human-observable phenomenon. Experimental findings indicate that incorporating a small set of HLIFs to a large set of low-level features yields very promising classification results with a standard linear SVM model. This can lead to better diagnostic accuracy of lesions at their infancy, thus potentially dramatically increasing survival rates of cancer patients.

The concept of HLIFs can be applied to any problem that involves extracting features that try to mimic or augment human perception.

Future Work

Future work involves mapping the HLIF scores to intuitive labels for user comprehension. The data will also be expanded and a statistical analysis of the feature space will be conducted. HLIFs to describe asymmetry and colour patterns will also be designed, and this set will be evaluated as a feature space for a diagnostic aid system.

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References