Modeling the Dermoscopic Structure Pigment Network Using a Clinically Inspired Feature Set

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Introduction

This work follows a relatively new trend in clinical dermatology: to identify specific ‘dermoscopic structures’ in the lesions such as the pigment network which is then used to arrive at a diagnosis. A pigment network (PN) can be classified as either Typical or Atypical and the goal is to automatically classify a given image to one of three classes: Absent, Typical (TPN), or Atypical (APN).

TPN: “a light-to-dark-brown network with small, uniformly spaced network holes and thin network lines distributed more or less regularly throughout the lesion”

APN: “a black, brown or grey network with irregular holes and thick lines”

Method Overview

An overview of our method for the identification and classification of PN is given in the following figure. We describe 4 main steps: pre-processing, hole detection, net detection, and feature extraction and classification.

Pre-processing

The image is first enhanced so that the PN is more visible. A contrast-limited adaptive histogram equalization is used. Images are then sharpened by subtracting a blurred version of the image from itself. Next, in order to prevent unnecessary analysis of the pixels belonging to the lesion, lesions are segmented using Wighton et. al.’s method [1] which employs supervised learning and a random walker algorithm. The output of the segmentation is a lesion mask which indicates which pixels belong to the lesion.

Hole Detection

To find the holes of the PN, we used our previous work [2] which employs a Laplacian of Gaussian (LoG) edge detector to create a graph-based structure which is used to identify holes of the PN. The result of this process is a ‘hole mask’ which indicates which pixels belong to the holes of the PN. Using the extracted holes, a PN-graph is created by connecting close holes.

Feature Extraction and Classification

Based on our working definitions of TPN and APN, we use the resulting lesion, hole, and net masks to propose a set of features capable of discriminating between the 3 classes (Absent, Typical and Atypical). We propose a set of structural (shape), geometric (spatial), chromatic and textural features.

Structural Features: Diagnostically important characteristics of an Atypical network include the thickness and variation in thickness of net as well as the size and variation in size of network holes. We compute the size and length and thickness of the net. Our features are the mean, standard deviation and ratio (mean/std) of the nets. We also compute the mean, standard deviation and ratio (mean/std) of the number of holes. We also include the ratio of the network size to the lesion size.

Geometric Features: Clinically, there is an emphasis on the ‘uniformity’ of the network in order to differentiate between TPN and APN. We have proposed the feature ‘density ratio’ of holes which, while useful in discriminating between the absence and presence of a pigment network, does not reliably discriminate between the TPN and APN. We include ‘density ratio’ of holes as a feature, as well as a new feature, ‘hole irregularity’. This feature is computed by constructing a graph as in [2] where two holes are connected if they are less than 3 times the average diameter of the holes. ‘Hole irregularity’ is then the number of edges in this graph.

Chromatic Features: Color also plays a crucial role in clinical diagnosis. We therefore convert the image to HSV colourspace and compute features over each channel as well as the original green channel of the image. In each channel, for the hole, net and lesion masks respectively we compute the mean, standard deviation and ratio (mean/std) of the intensity values. Additionally, we propose a new chromatic feature called the ‘atypicality measure’ which is the sum of the intensity values over the green channel of the pixels in the net mask.

Textural Features: We use five of the classical statistical texture measures: entropy, energy, contrast, correlation and homogeneity which are derived from a grey level co-occurrence matrix. We extracted these features over the entire lesion and over the pigment network.

Results

These 69 features are fed into a classifier so that new images can be classified. We employ the WEKA’s implementation SimpleLogistic. We applied the method described above to a set of 436 dermoscopic images taken from two atlases of dermoscopy. The following table compares accuracy of our proposed features with Di Leo et al.’s 13 features using the same set of 436 images.

<table>
<thead>
<tr>
<th>Absent-Typical-Atypical Classification</th>
<th>Precision</th>
<th>Recall</th>
<th>F-measure</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absent</td>
<td>0.905</td>
<td>0.950</td>
<td>0.927</td>
<td>-</td>
</tr>
<tr>
<td>Typical</td>
<td>0.787</td>
<td>0.702</td>
<td>0.700</td>
<td>-</td>
</tr>
<tr>
<td>Atypical</td>
<td>0.750</td>
<td>0.694</td>
<td>0.721</td>
<td>-</td>
</tr>
<tr>
<td>Weighted Avg</td>
<td>0.820</td>
<td>0.823</td>
<td>0.821</td>
<td>0.823</td>
</tr>
<tr>
<td>Di Leo et al. [3]</td>
<td>0.709</td>
<td>0.711</td>
<td>0.709</td>
<td>0.719</td>
</tr>
</tbody>
</table>

Conclusion and Future Work

We have described techniques to identify the dermoscopic structure “pigment network”. Furthermore, we have proposed and validated a set of clinically motivated features over these sub-structures suitable for classification. Our feature set has proven to be robust, outperforming previous work on a more inclusive ‘real-world’ dataset consisting of 436 images, which is the largest validation to date on the 3-class problem.

References