Illumination Correction in Dermatological Photographs using Multi-stage Illumination Modeling for Skin Lesion Analysis

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Agenda

- Introduction
- Methodology
- Experimental Results
- Conclusion

Introduction

- Melanoma is a form of skin cancer
- 1 in 74 men and 1 in 90 women develop melanoma in their lifetime (Canadian Cancer Statistics 2008)
- Need for automated system to assess patient's risk of melanoma

Problem

- Objective is to develop algorithm to remove illumination variation in skin lesion images
  - Pre-processing step before identifying lesion boundaries and classifying lesion risk

Example

- Example lesion image with illumination variation

Existing Algorithms

- Assume illumination-reflectance model
- General illumination correction
  - Gaussian filters
  - Morphological operators
- Specific to dermatological images
  - Fit to a parametric surface (Cavalcanti et al, 2010)

Illumination-Reflectance Model

- Assumes that illumination and reflectance (detail) components are multiplicative

$$v(x, y) = i(x, y) \cdot r(x, y)$$

- After log transform, illumination and reflectance are additive

$$v_{log}(x, y) = i_{log}(x, y) + r_{log}(x, y)$$

Algorithm Overview

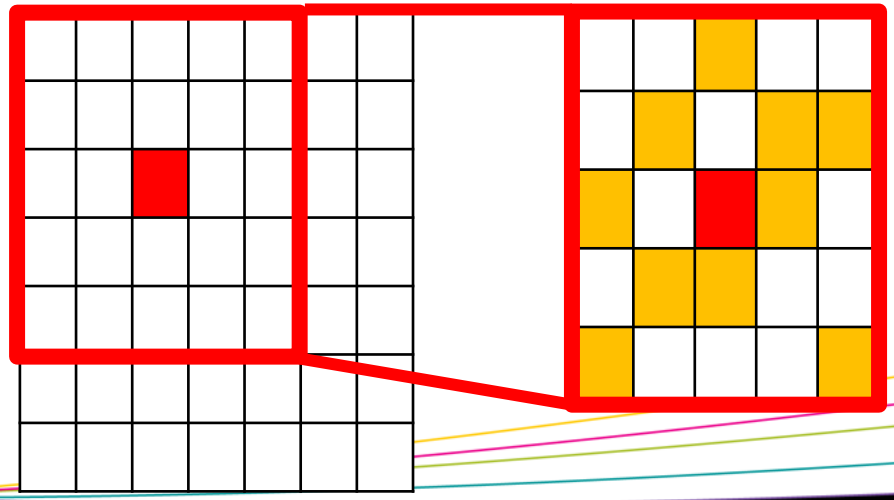
1. Monte Carlo algorithm for an initial estimate of illumination component
2. Parametric curve for the final estimate of illumination component
3. Correct for illumination in the original image

1. Monte Carlo Illumination Estimation

- Estimating illumination given the *V* channel

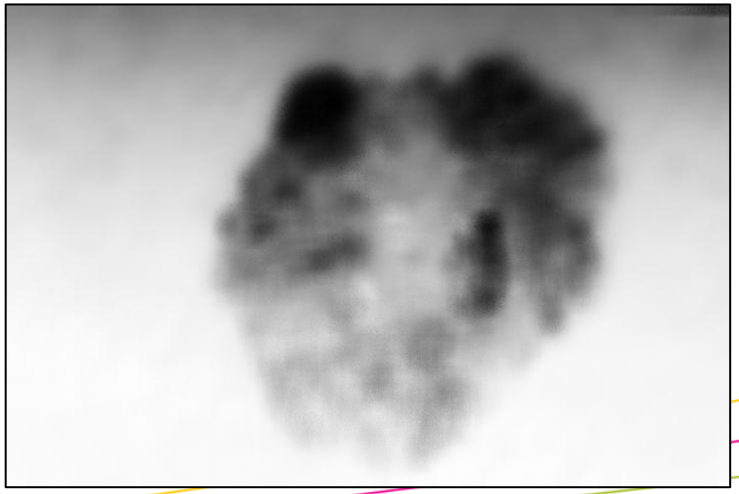
$$\hat{i}_{log} = \int i_{log} p\left(i_{log} \middle| v_{log}\right) d i_{log}$$

1. For each pixel in the image:
   – Randomly draw samples from a search space surrounding the pixel of interest



1. Monte Carlo Illumination Estimation (cont.)

2. For each selected pixel:
   – Compute acceptance probability based on sum-of-squared differences of neighbourhoods
3. Build posterior distribution as a weighted histogram
4. Estimate the pixel's illumination component



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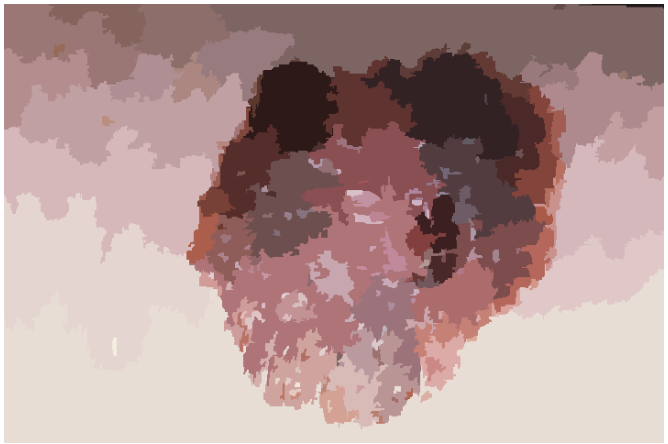
2. Parametric Illumination Estimation

- Fit initial map to a parametric curve
  - Estimate which pixels are normal skin pixels using region merging algorithm
  - Classify regions touching corners as “skin”



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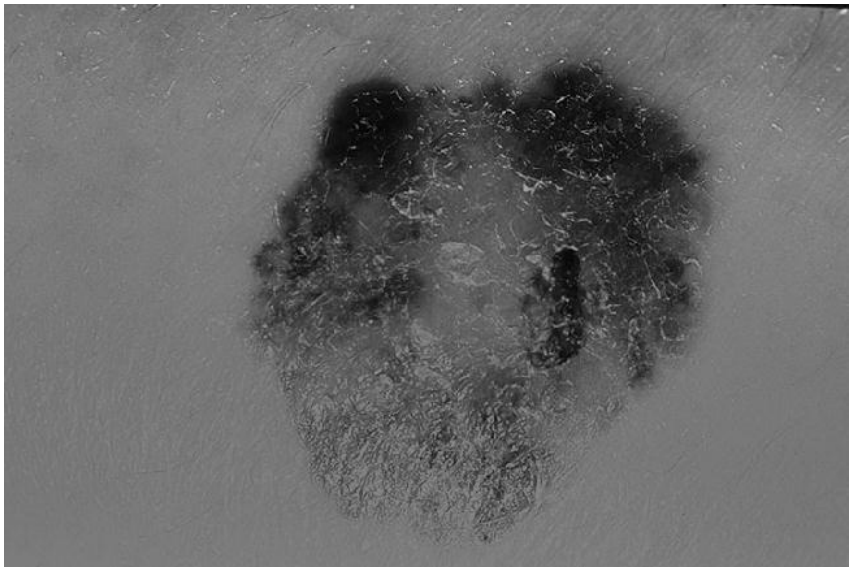
2. Parametric Illumination Estimation (cont.)

- Fit a quadratic surface to skin pixels
- Example of final illumination estimation

$$i'(x, y) = P_1 x^2 + P_2 xy + P_3 y^2 + P_4 x + P_5 y + P_6$$

3. Reflectance Map Estimation

- Estimate reflectance component
- Combine with original *H* and *S* channels

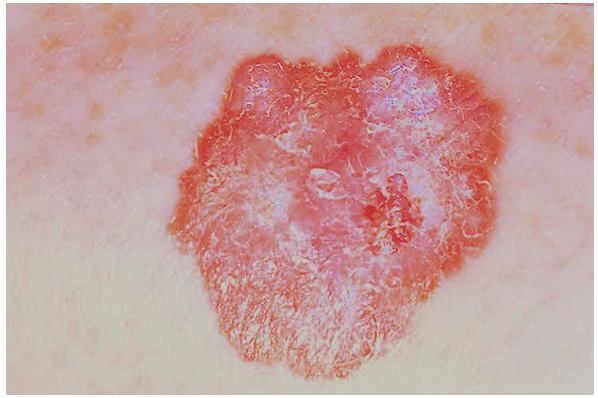
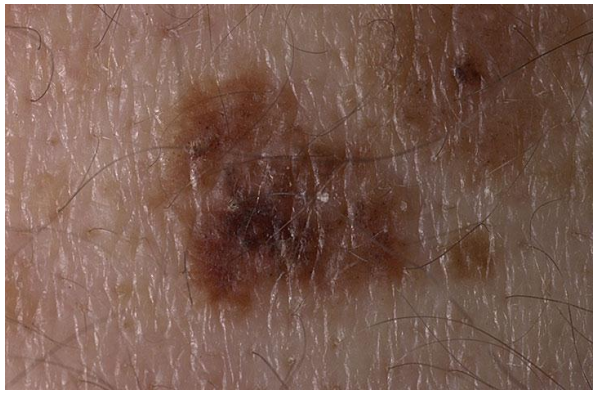
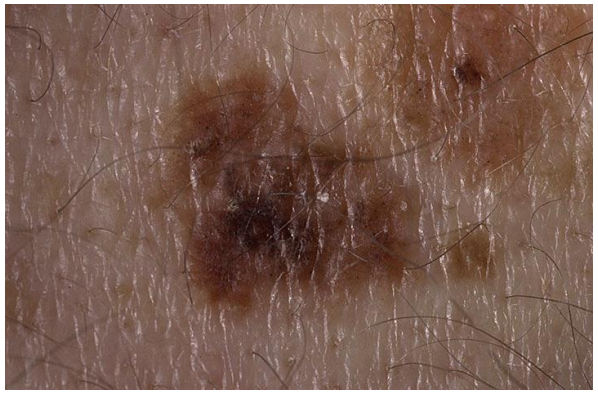


Experimental Results

- Compared with skin lesion illumination correction algorithm proposed by Cavalcanti et al. (2010)
- Used coefficient of variation to quantify improvements

$$cv = \frac{\sigma}{\mu}$$

Examples

Original	Cavalcanti et al.	Proposed Approach
		
cv = 0.206	*cv* = 0.001	*cv* = 0.064
		
cv = 0.211	*cv* = 0.312	*cv* = 0.130

Examples (cont.)

Original

cv = 0.309

Cavalcanti et al.

cv = 0.260

Proposed Approach

cv = 0.170

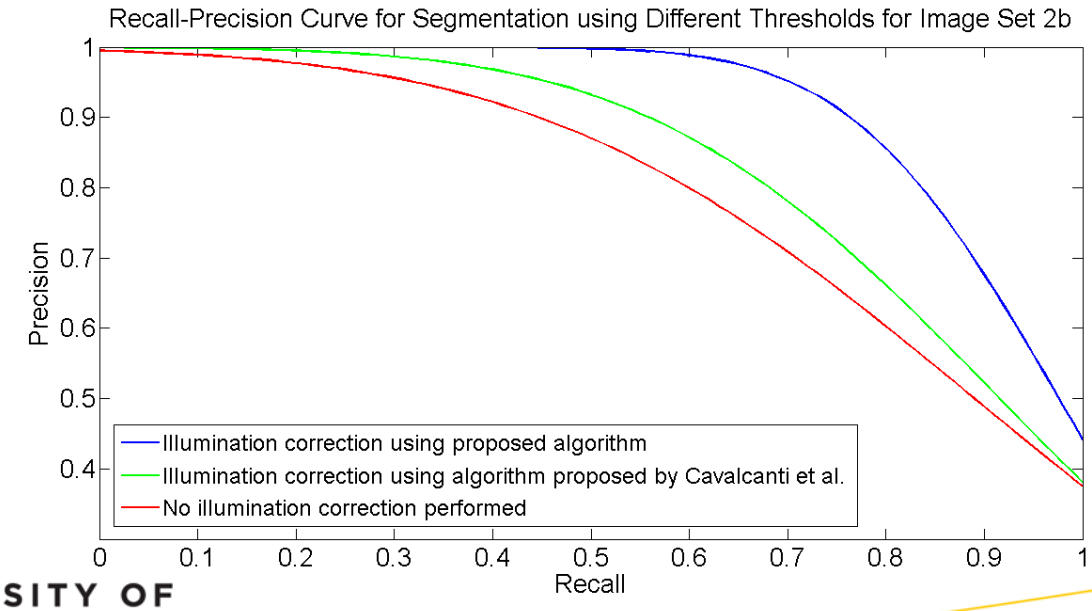
cv = 0.240

cv = 0.211

cv = 0.076

Segmentation Example

- Segment using simple threshold
- Recall and precision measured at different threshold levels



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Conclusion

- Must correct for illumination variation
- Multi-stage illumination modeling
  - Initial non-parametric Monte Carlo illumination model
  - Final parametric surface model
- Results show decrease in coefficient of variation and improved segmentation

Thanks!
Questions?

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