



Extracting High-Level Intuitive Features (HLIF) For Classifying Skin Lesions Using Standard Camera Images

Robert Amelard,
Alexander Wong, David A. Clausi
Vision and Image Processing Group
University of Waterloo

Motivation

- Melanoma: deadliest skin disease
- Early detection
 - 5-year survival rate
- Dermatologists
 - Time-constrained
 - 82.6% correct malignant*
 - 70.0% correct benign*

Outline

- Clinical/Research Background
- Features
- Experiments
- Conclusions and Future Work

Clinically: ABCD

- **Asymmetry**
Border Irregularity
Colour Patterns
Diameter



- **High-Level Intuitive Features (HLIFs)**
 - Modeled from human-observable phenomena
 - Quantitatively describe ABCD

Clinical Decision Support System



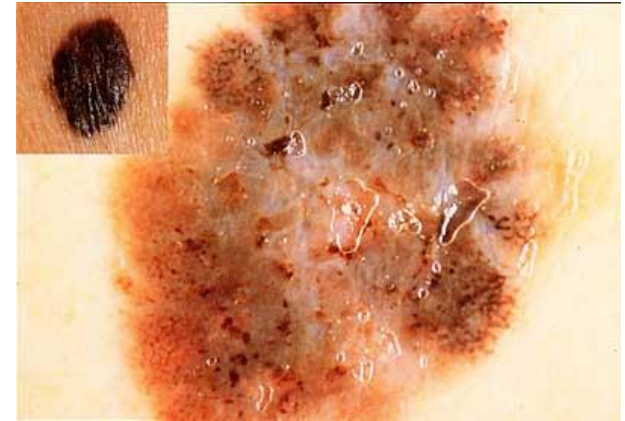
- Asymmetry
- Border Irregularity
- Colour Patterns
- Diameter



Malignant
Benign

Prior Work

- Dermoscopic images
 - Most prominent in literature
 - Limited clinical use*



Source: www.medilor.be

- Standard images
 - Very new
 - Low barrier to adoption
 - Technical challenges

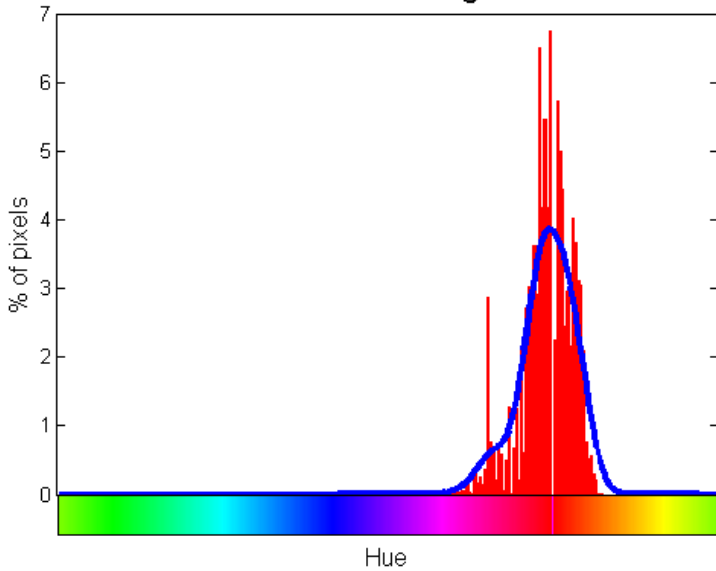


What is State of the Art?

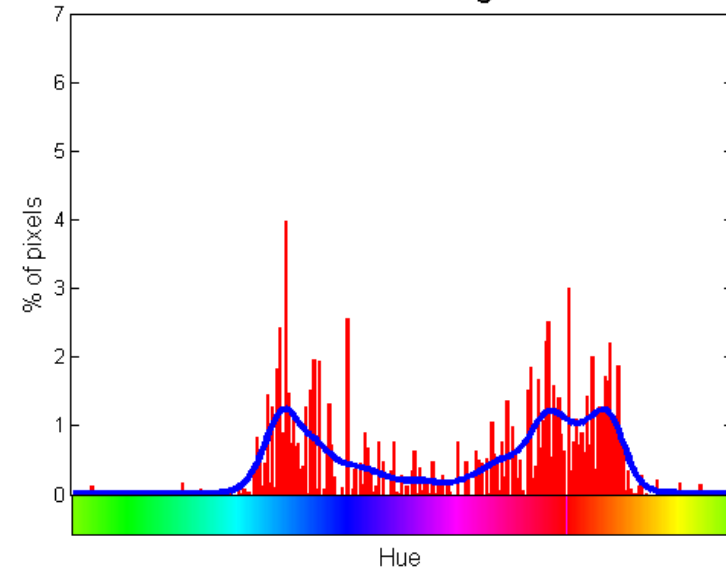
- 52 low-level features*
 - Abstract mathematical/statistical descriptions
- Computationally complex
- Sub-optimal results

Proposed Features: Asymmetry

Normalized Histogram

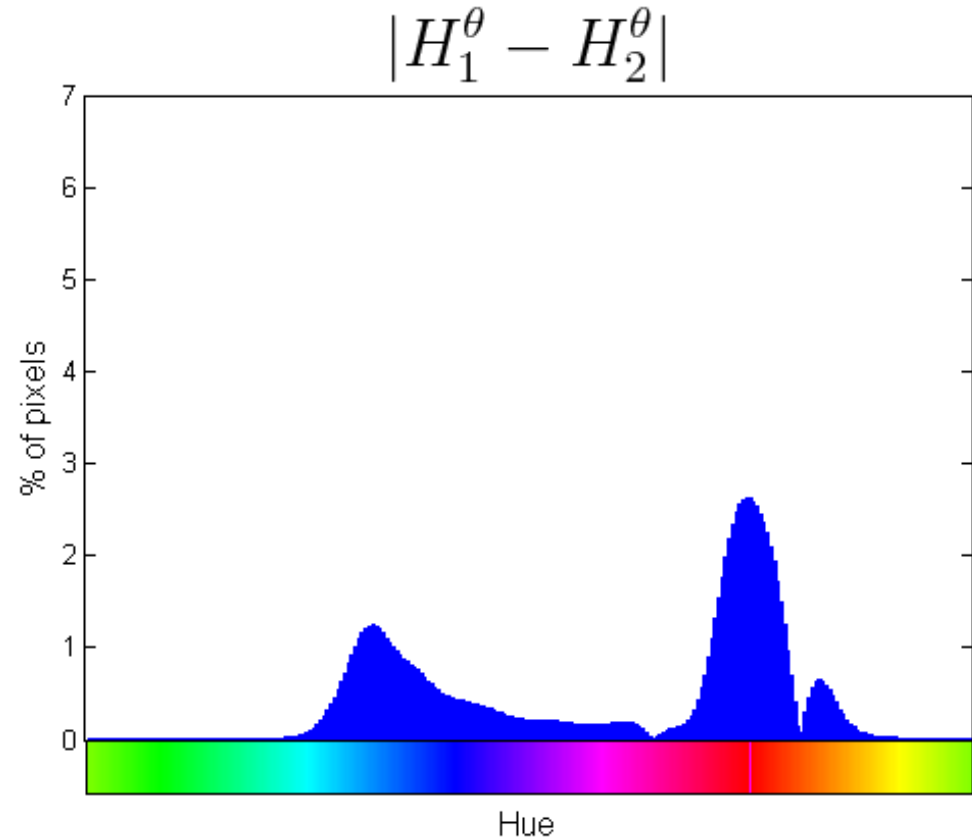
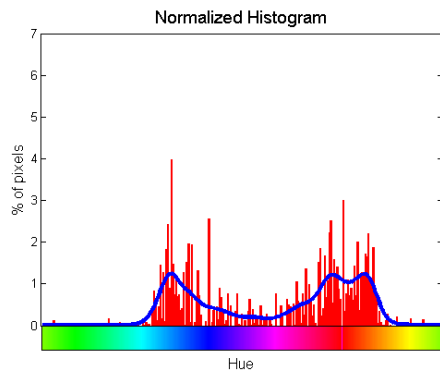
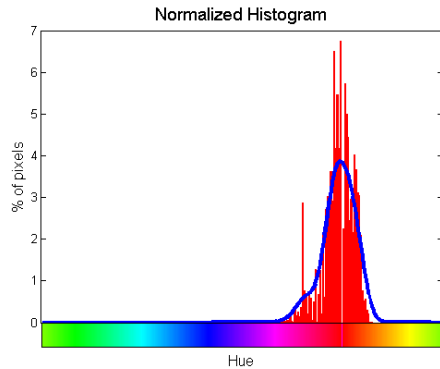


Normalized Histogram



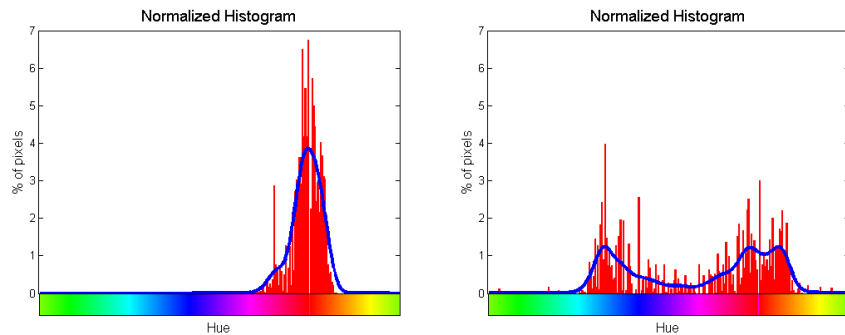
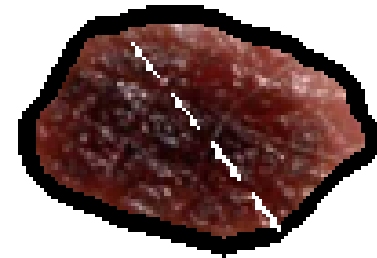
$$f_1^A = \max_{\theta} \left\{ \frac{1}{2} \sum_{i=1}^{nbins} |H_1^{\theta}(i) - H_2^{\theta}(i)| \right\}$$

Proposed Features: Asymmetry

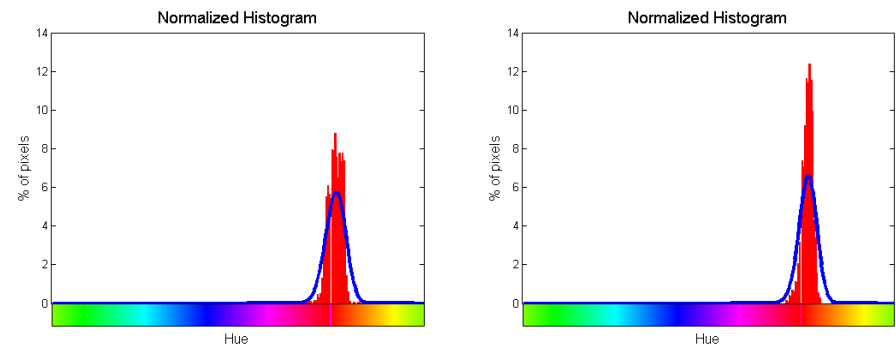


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Example

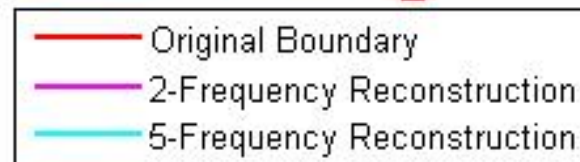
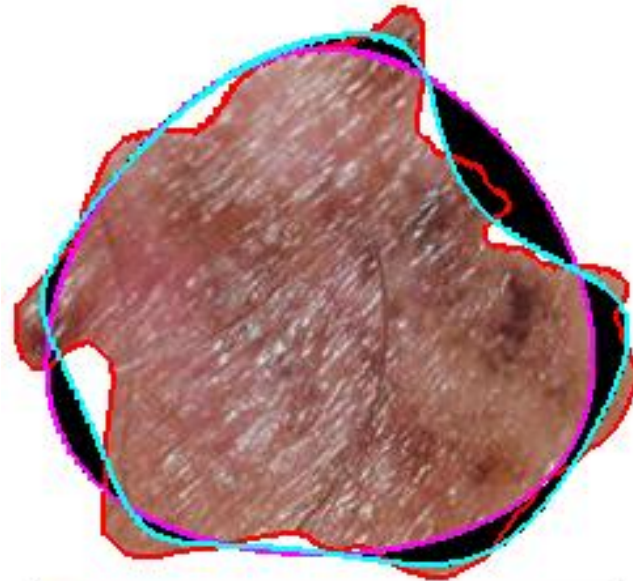


$$f_1^A = 0.5300$$



$$f_1^A = 0.0960$$

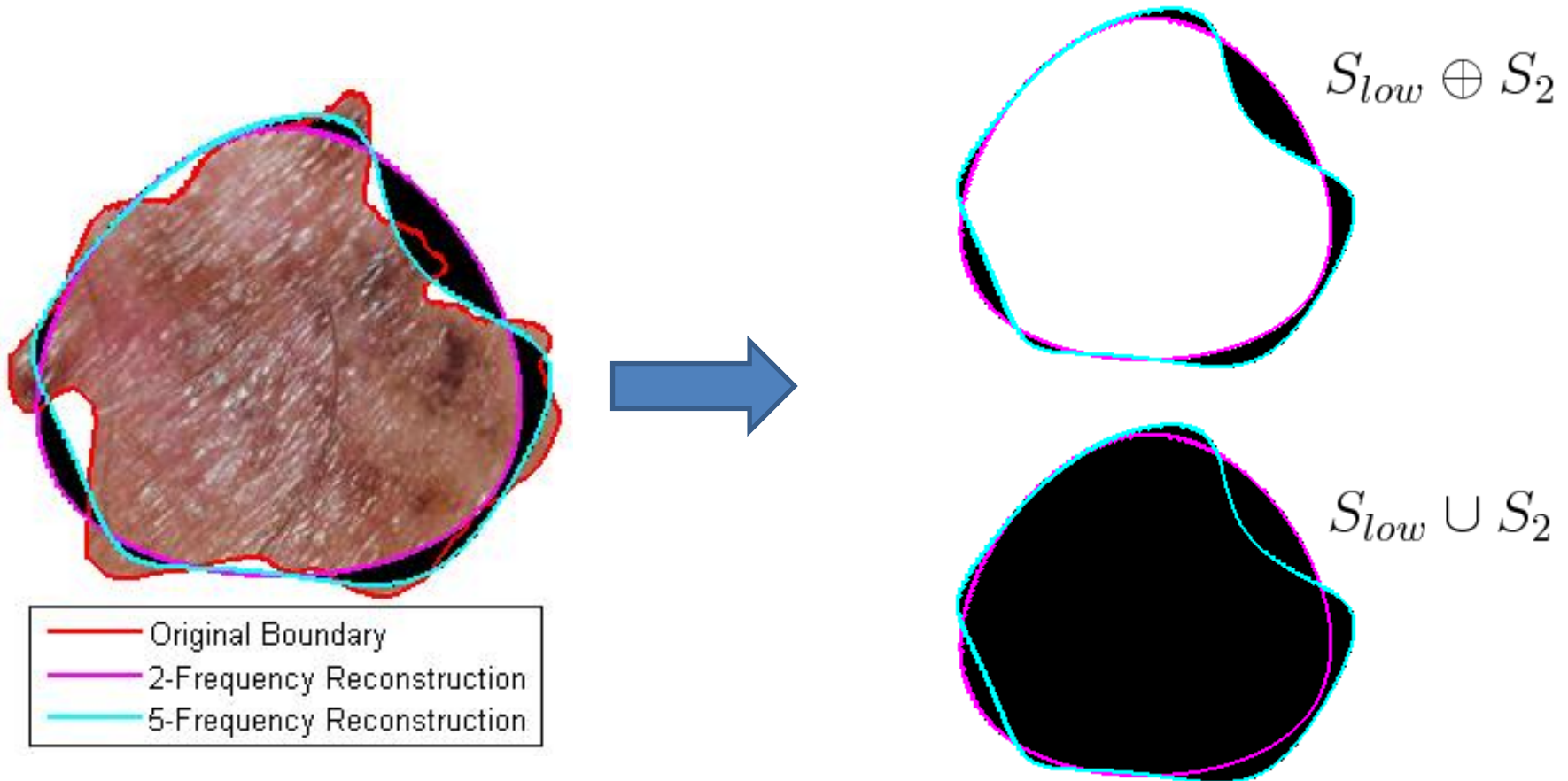
Proposed Features: Asymmetry



$$f_2^A = \frac{\text{area}(S_{low} \oplus S_2)}{\text{area}(S_{low} \cup S_2)}$$

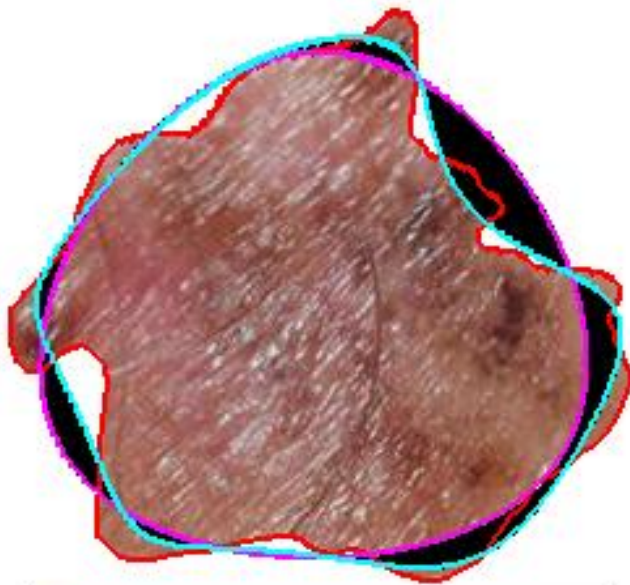
(Updated)

Proposed Features: Asymmetry



$$f_2^A = \frac{\text{area}(S_{low} \oplus S_2)}{\text{area}(S_{low} \cup S_2)} \quad (\text{Updated})$$

Example



— Original Boundary
— 2-Frequency Reconstruction
— 5-Frequency Reconstruction

$$f_2^A = 0.1199$$



— Original Boundary
— 2-Frequency Reconstruction
— 5-Frequency Reconstruction

$$f_2^A = 0.0801$$

Proposed Features: Asymmetry

Original Lesion



Major Axis (L_1)



Minor Axis (L_2)



$$f_3^A = (A_1 - A_2)/A \text{ with respect to } L_1,$$

$$f_4^A = (A_1 - A_2)/A \text{ with respect to } L_2,$$

$$f_5^A = (A_1 - A_2)/A_2 \text{ with respect to } L_1,$$

$$f_6^A = (A_1 - A_2)/A_2 \text{ with respect to } L_2$$

Results

- 206 images from Dermatology Information System & DermQuest
- Linear Support Vector Machine
 - **Sensitivity**: % malignant cases identified
 - **Specificity**: % benign cases identified

Description	# features	Sensitivity	Specificity
Cavalcanti (Asym)	11	71.43%	58.62%
Proposed (Asym)	6	79.83%	68.97%

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New Feature Set	54	91.60%	80.46%

(Updated)

Conclusions

- High-level intuitive features (HLIFs) result in understandable, low-dimensional feature spaces
- Adding HLIFs to low-level features generates very high success metrics
- HLIFs are generalisable!

Future Work

- Design HLIFs to describe Border Irregularity, Colour Patterns
- Test on larger data set, more statistical meaning
- Diagnosis can be “queried” by doctor for rationale
- Saving more lives through early detection

Thank You!

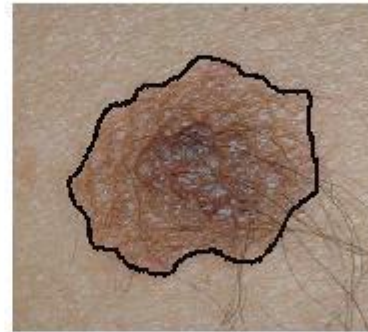
ramelard@uwaterloo.ca

<http://vip.uwaterloo.ca>

Sources of Error



Missed malignant cases



Missed benign cases