A reliable skin mole localization scheme

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IEEE Workshop on MMBIA
October 15 2007

Outline

- Overview of the system
- Skin detection
- Hair removal
- Mole detection
- Experimental results
- Conclusion

The Goal of the System

Input Image

Output Image

Reliably detect moles images taken under a less constrained imaging setting

Motivation

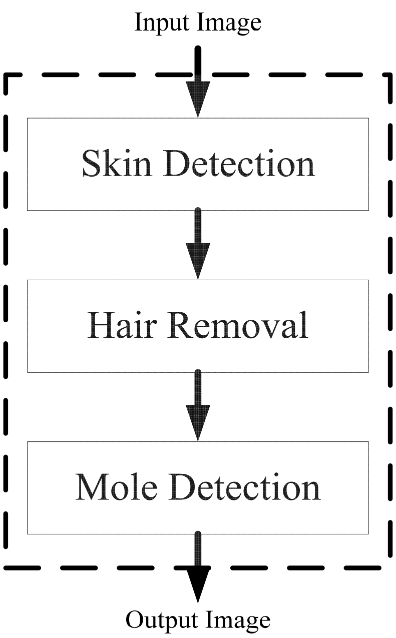
- Important cues in melanoma detection is the change of moles' size and their constellation pattern.
- Mole localization and registration is both time-consuming and prone to human error
- Fully automated mole diagnosis system requires a mole localization step prior to any analysis

Previous Work

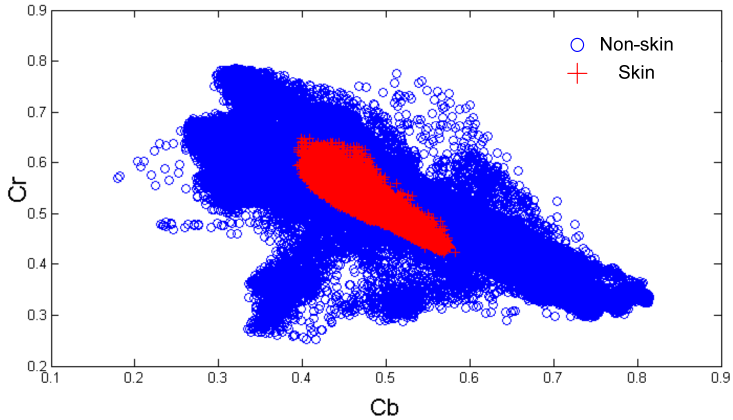
- Mole localization in images taken under a constrained setting [Lee et al. 2005]

- Skin singularity detection for face recognition [Pierrard et al. 2007]

System Overview

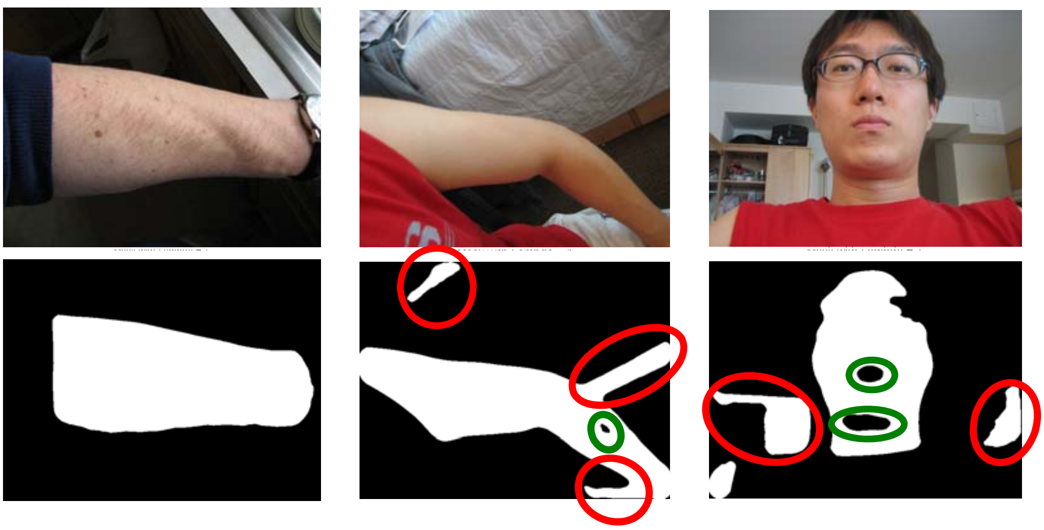


Skin Detection



- Neyman-Pearson criterion for skin detection
- A median filter is used to reduce salt-and-pepper islands

Skin Detection Result

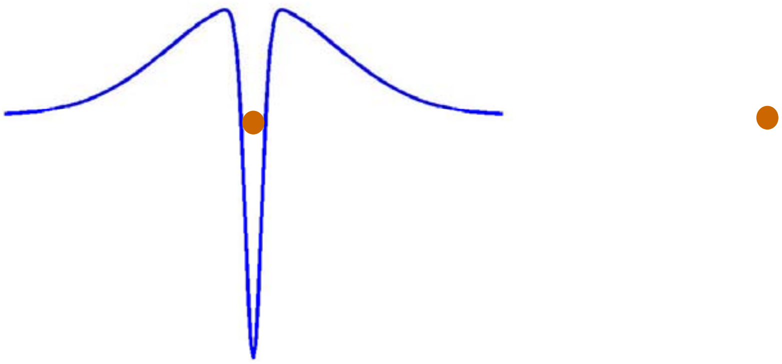


: False Positive

: False Negative

Mole Candidate Detection

- Moles are modeled as a dark circular region



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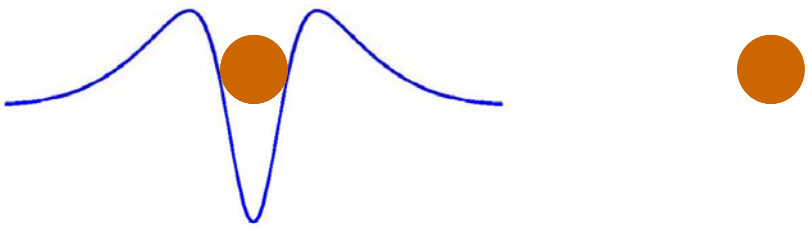

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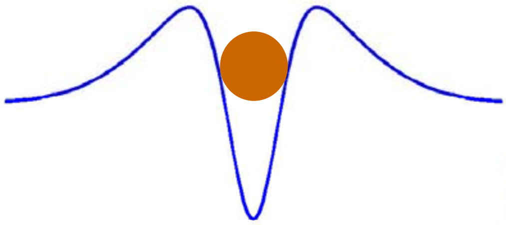
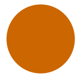
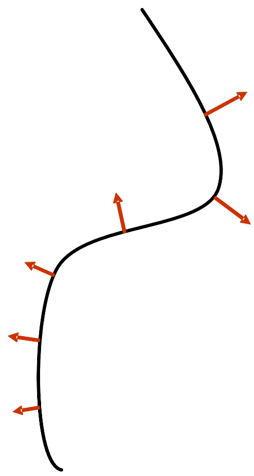




- Could be problematic if hair is present

Hair Removal

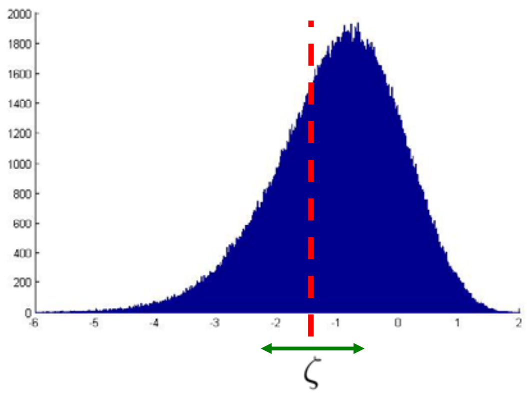


Removal of strands in an arbitrary orientation

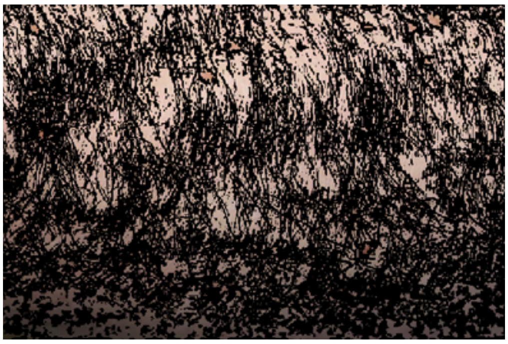
Hair Removal

$$\boxed{\log(\max_{\phi}(F_{\phi}(x))) \geq \zeta(im)}$$

Histogram of the Log Maximum Gradient



Thresholded Image

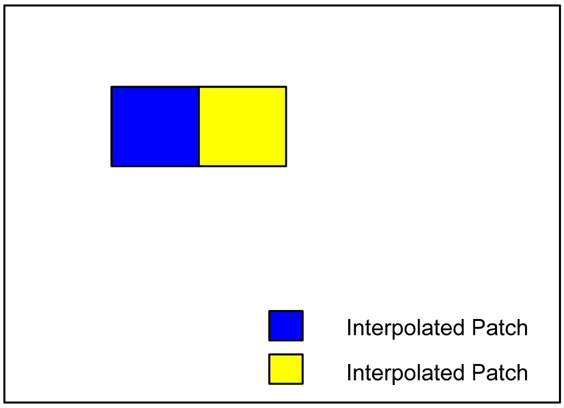


Hair Removal

Skin region reconstruction with a GMRF

$$p(x) \propto \exp(-\alpha_2 \sum_{i \in V}(x_i - \frac{1}{|\mathcal{N}(x_i)|}\sum_{j \in \mathcal{N}(x_i)} x_j)^2)$$

$$\hat{x}_{MAP} = \arg\max p(x|y) = J^{-1}h$$



Hair Removal

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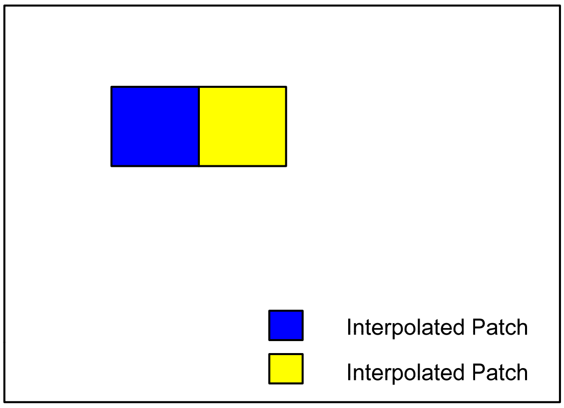

Blocky Artifacts!

Hair Removal

Skin region reconstruction with a GMRF

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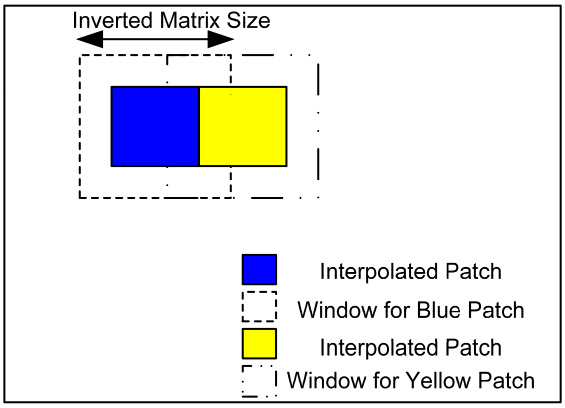


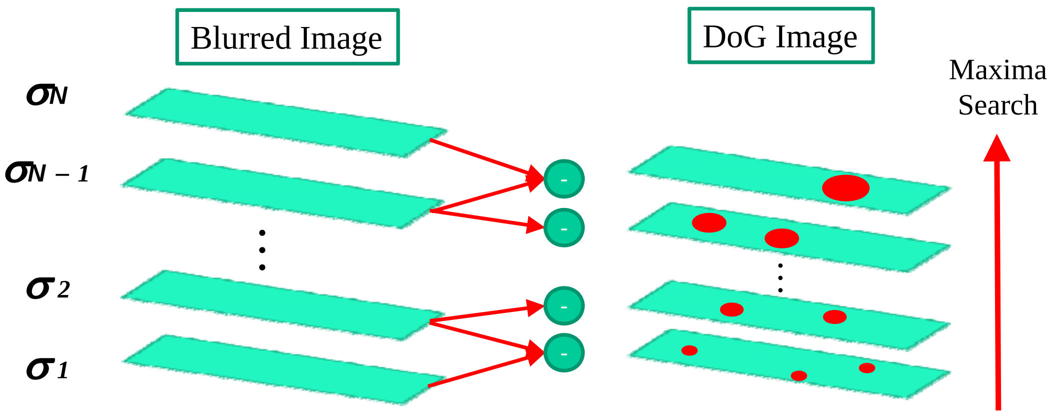
Hair Removal Result

Input Image

Proposed Scheme

Dull Razor [Lee et al. 97]

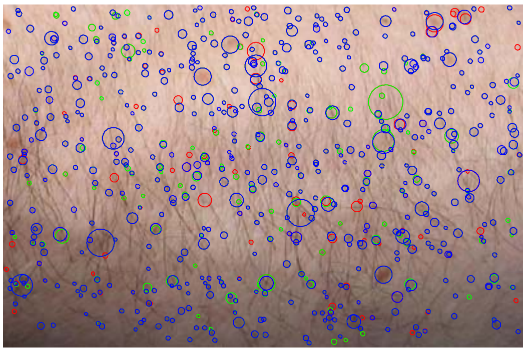
Mole Candidate Localization



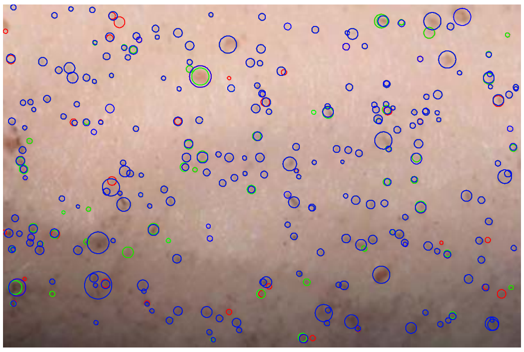
DoG scale-space maxima are mole candidates

Mole Candidate Localization Result

DoG Maxima
Before Hair Removal

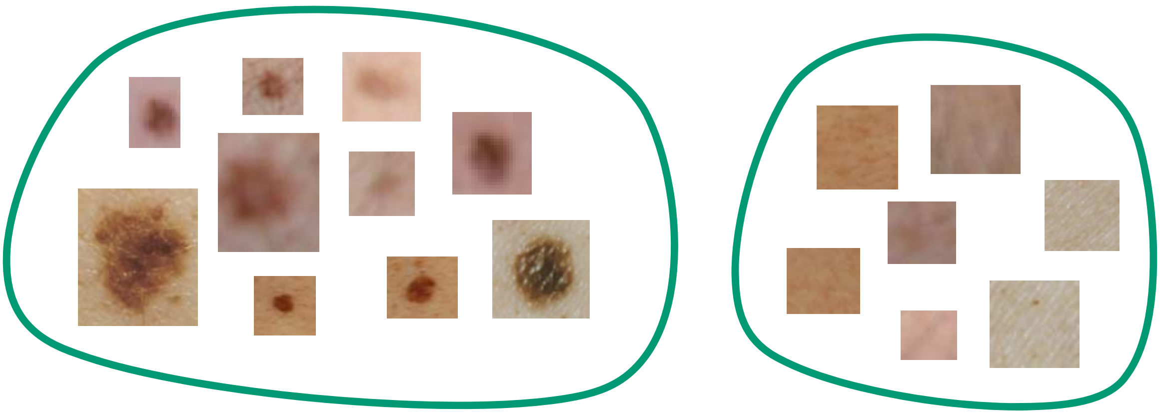


DoG Maxima
After Hair Removal



Less mole candidates to consider after removing the hair

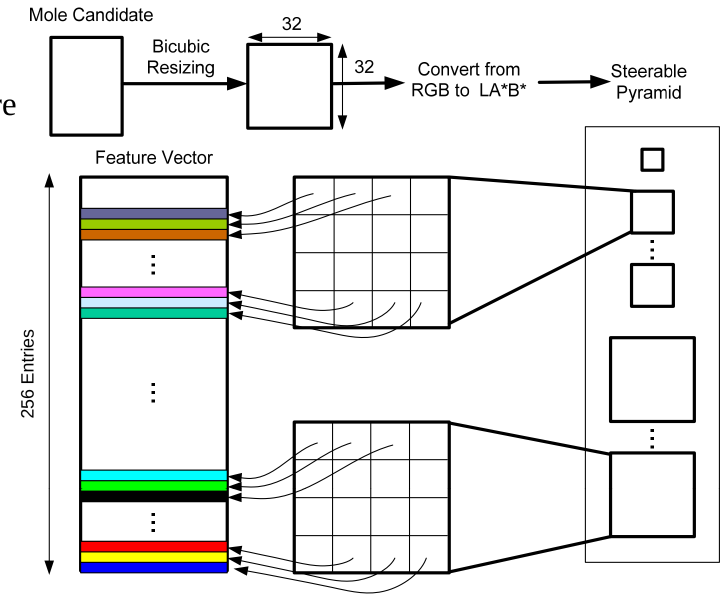
Mole Classification



- Assumption
  - Texture unique to moles is present in the image
  - Color information is present in the image

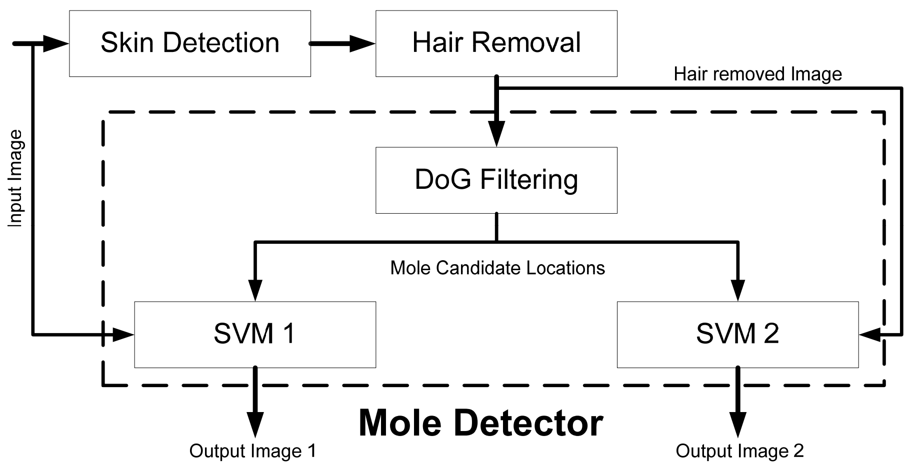
Classification with SVM

A steerable-pyramid-based feature vector is used to capture the texture and shape information.



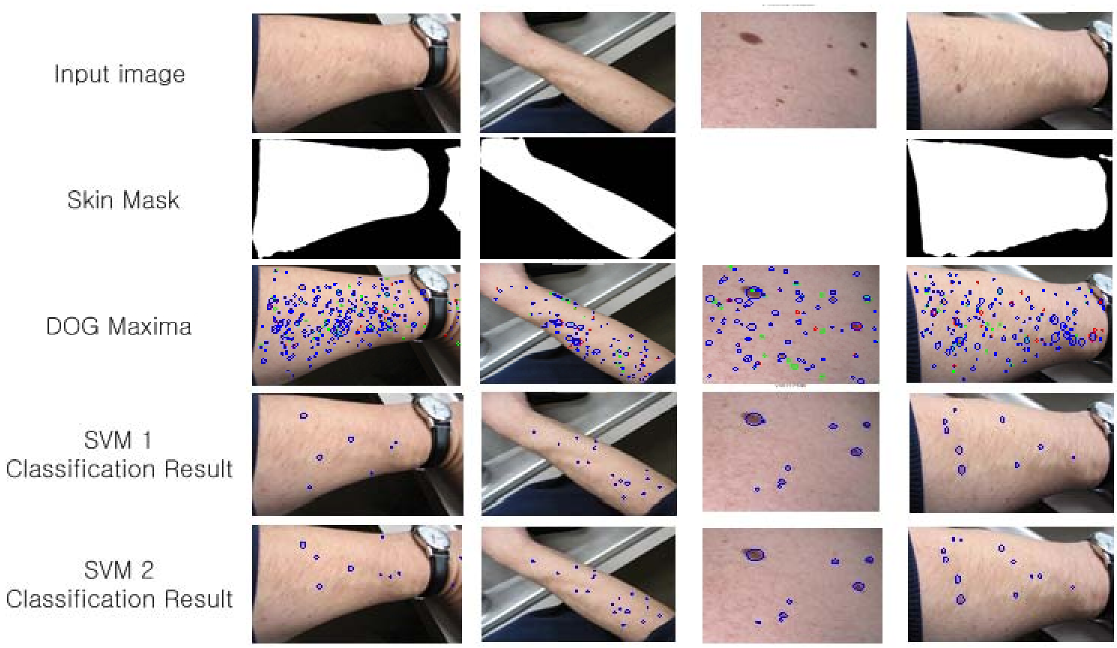
SVM is trained with 132 mole, 447 non-mole images

Experiment Setup



Two types of SVMs are trained to test how the hair removal step benefits the mole recognition rate

Mole Localization Result



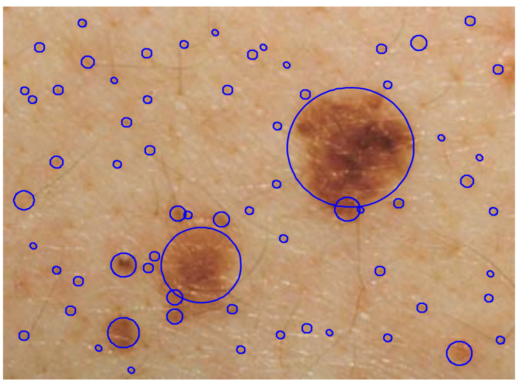
SVM Performance

SVM 1		SVM 2	
S	DA	S	DA
79.4%	76.5%	84.7%	79.3%

$$Sensitivity = \frac{TP}{TM}$$

$$DiagnosticAccuracy = \frac{TP}{TM + FP}$$

Failure Case



Conclusion

- The proposed mole localization scheme can be used prior to an automatic mole analysis system
- Hair removal increases the mole localization rate
- User intervention, as well as a constrained imaging condition, can increase the reliability

Acknowledgment: Funding from MSR and Samsung Scholarship Foundation