



Melanoma Skin Sample Imaging

- Diagnosis currently relies on biopsy and histopathology, with many false positives
- Melanin content carries information about metabolism and location of melanocytes
- New two-color pump-probe imaging distinguishes eumelanin and pheomelanin

Melanoma Diagnosis

- Among *most clinically challenging* cancer types to diagnose
- From 1990 to 2006, US cancer deaths decreased by 17%; melanoma death rates increased by 7%
- Early detection is *critical* for survival metastatic melanoma: 16%; local cancers: 98% (after five years)
- Diagnosis by biopsy and histopathology results in *discordant conclusions* (14% rate among pathologists)
- Erring on the side of caution *increases the rate of false positives*

New Imaging Modalities for Melanoma Detection and Classification

- Melanomas are amenable to optical diagnosis lesions are accessible and disease occurs close to skin surface
- Melanin carries information on metabolism and location of melanocytes • Eumelanin and pheomelanin content may act as markers for disease

Two-Color Pump-Probe Spectroscopy Imaging System [1]





Melanoma Classification from Hidden Markov Tree Features

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Interpulse Delay (ps)

The Structure of Skin Sample Images

- Different stages of melanoma exhibit different types of spatial image structure
- Hidden Markov trees (HMT) provide statistical model for image wavelet coefficients
- HMT parameters provide features capturing image structure, suitable for classification

Melanoma Classification by Melanin Concentration

Green: Pheomelanin; Orange: Eumelanin





Compound Nevi



- Concentration of melanin characteristic for different classes
- Minimum eumelanin content of 38% separates most melanomas from 75% of nevi samples [2]
- Single metric cannot distinguish between nevi or capture structural image information

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Hidden Markov Tree Models [3]



Parameters for each tree:

- Probability of small and large states for each scale:
 - $p_n^{\mathsf{S}} = p(\mathcal{S}_n = \mathsf{S}) \qquad p_n^{\mathsf{L}} = p(\mathcal{S}_n = \mathsf{L})$
- Variances of Gaussians for small and large states for each scale: $\sigma_{S,n}, \sigma_{L,n}$



Melanoma Lesion type

One tree per orientation (H, V, D)

Hidden Markov Tree-Based Image Features

Three detection/classification feature types:



Collect probabilities of small state $p_{\Omega,n}^{S}$ for each orientation and scale 512×512 -pixel skin sample images produce vectors of size 27(F1)/54(F2/F3) 2ν -Support Vector Machines for Neyman-Pearson-Style classification [3]

Test	Success Rate	Detection Rate	False Alarm Rate
Melanoma vs. Nevi	73%	72%	74%
Melanoma vs. Nevi and Sebhorreic Keratoses	61%	62%	60%
Invasive Melanoma vs. Nevi	57%	54%	57%
In Situ Melanoma vs. Nevi	72%	73%	72%
Melanoma vs. Benign	59%	60%	58%
Melanoma vs. Dysplastic	56%	52%	60%

References

- in *ICASSP*, Toulouse, France, May 2006, vol. V, pp. 589–592.



Melanoma Detection & Classification

• Selection of small state likelihood among scales as feature vector • Features quantify presence/absence of image structure at multiple scales • Features distinguish between concentrated and disseminated content

• F1: One HMT for sample image depicting only total melanin concentration (no discrimination of eumelanin and pheomelanin)

• F2: Two HMTs on eumelanin and pheomelanin concentration images (no discrimination of chemically homogeneous and heterogeneous regions) • F3: Two HMTs on % eumelanin and pheomelanin concentration images

(1) D. Fu, T. Ye, T. E. Matthews, G. Yurtsever, and W. S. Warren, "Two-color, two-photon, and excited-state absorption microscopy," J. Biomedical Optics, vol. 12, no. 5, 2007

(2) T. E. Matthews, I. R. Piletic, M. A. Selim, M. J. Simpson, and W.S. Warren, "Pump-probe imaging differentiates melanoma from melanocytic nevi," Science Translational Medicine, vol. 3, no. 71, Feb. 2011.

(3) M. S. Crouse, R. D. Nowak, and R. G. Baraniuk, "Wavelet-based statistical signal processing using Hidden Markov Models," IEEE Trans. Signal Processing, vol. 46, no. 4, pp. 886–902, Apr. 1998.

(4) M. A. Davenport, R. G. Baraniuk, and C. D. Scott, "Controlling false alarms with support vector machines,"