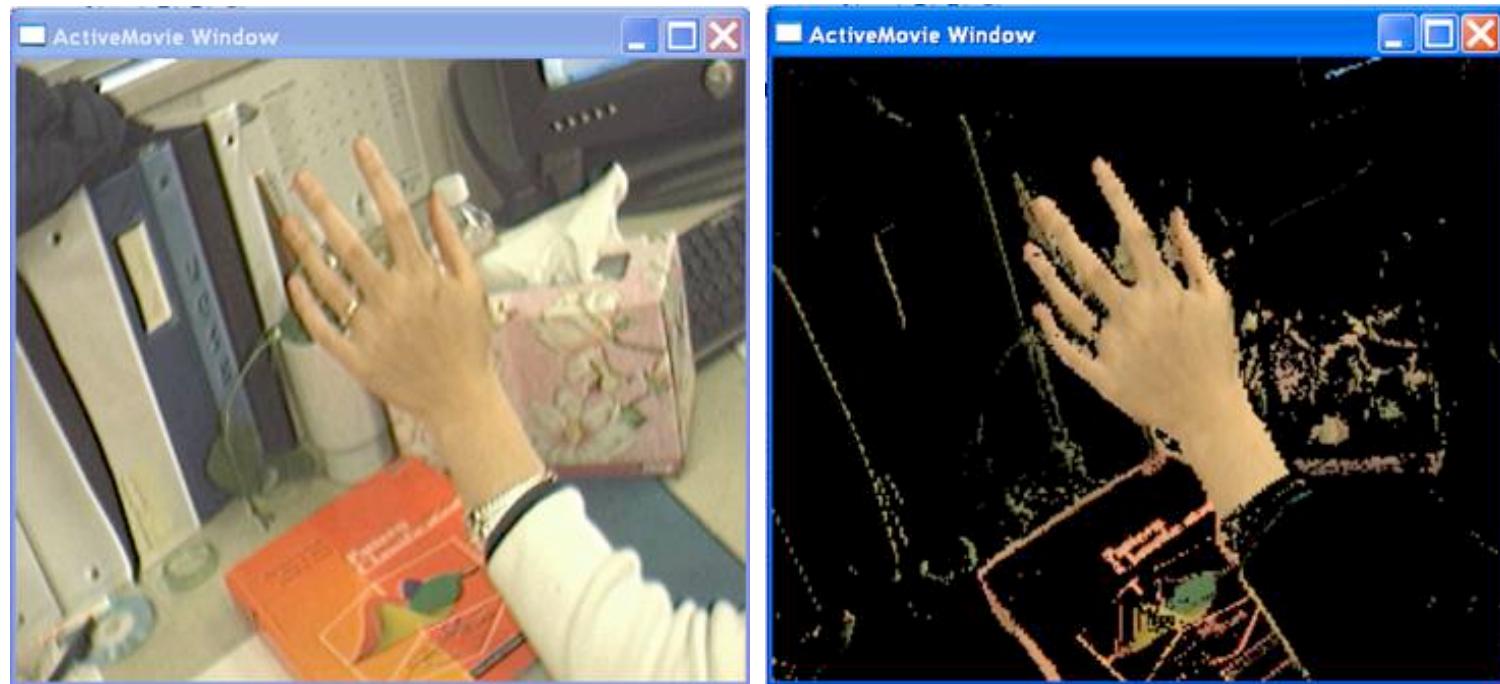


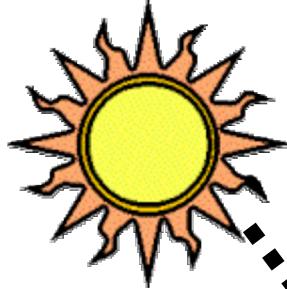
# Lecture 27:

## Skin Color



# Review: Light Transport

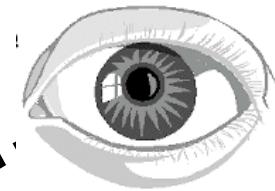
Source emits photons



Photons travel in a straight line



And then some reach an eye/camera and are measured.

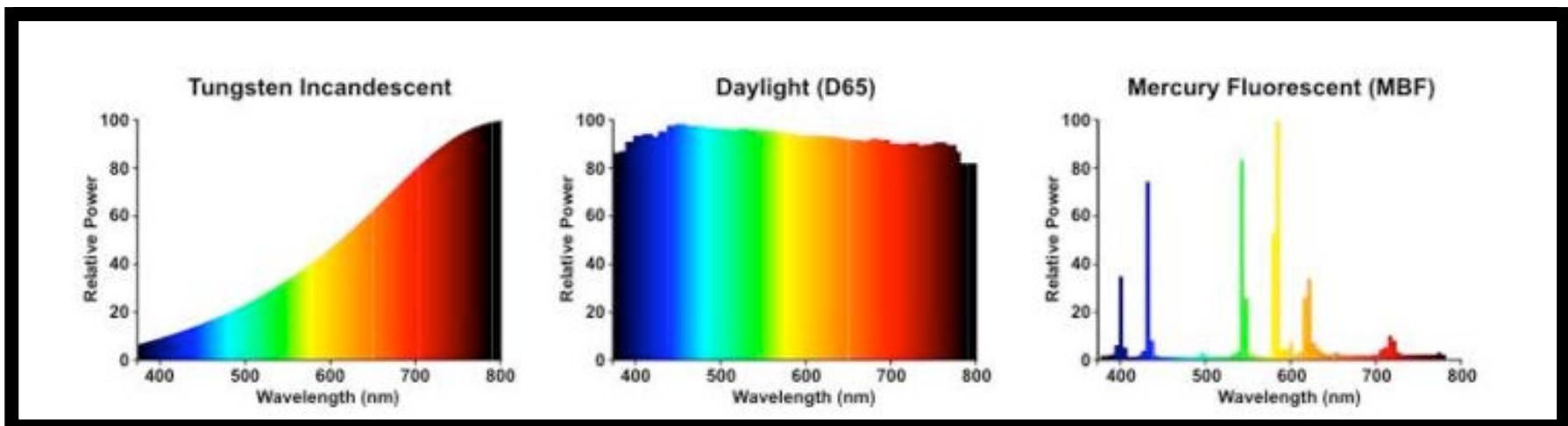
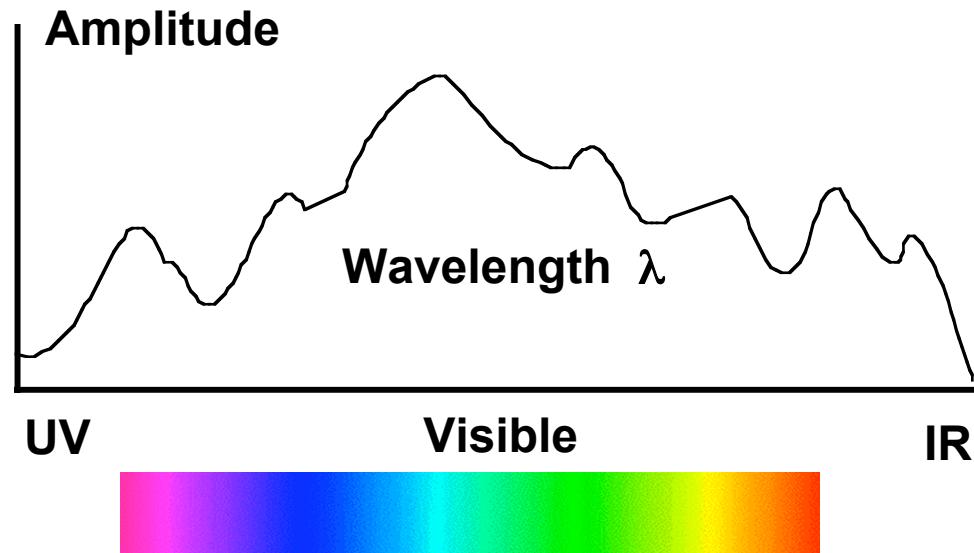


They hit an object. Some are absorbed, some bounce off in a new direction.

# Color of Light Source

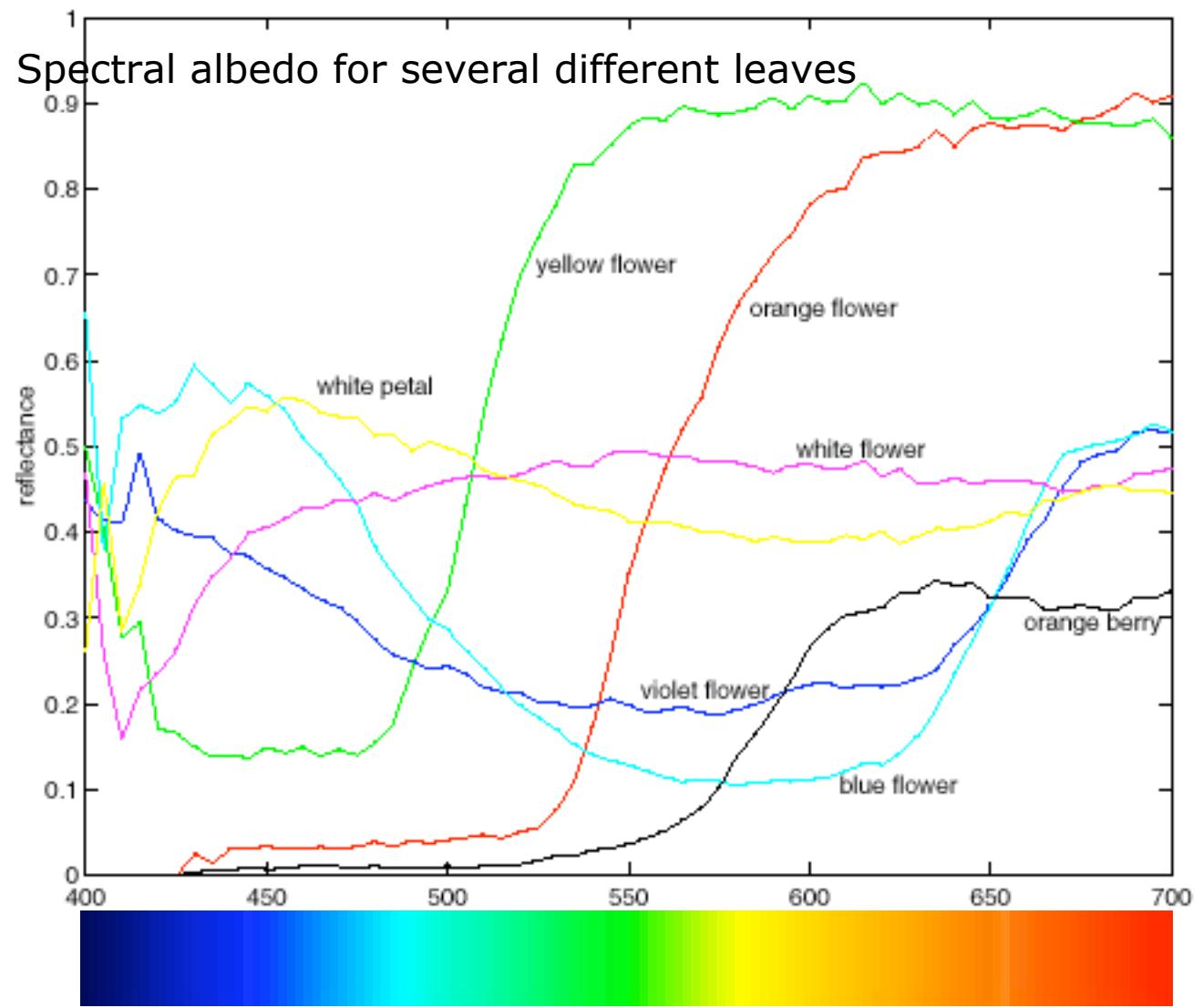
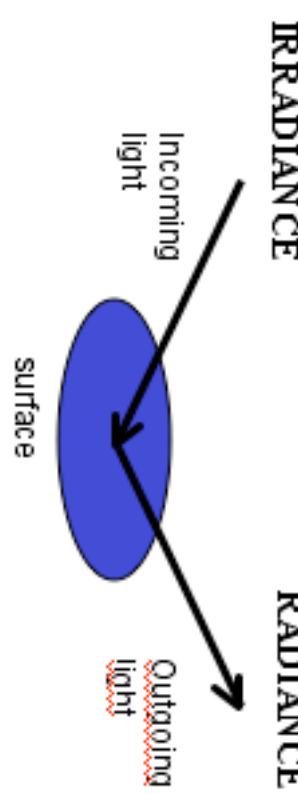
## Spectral Power Distribution:

Relative amount of light energy at each wavelength

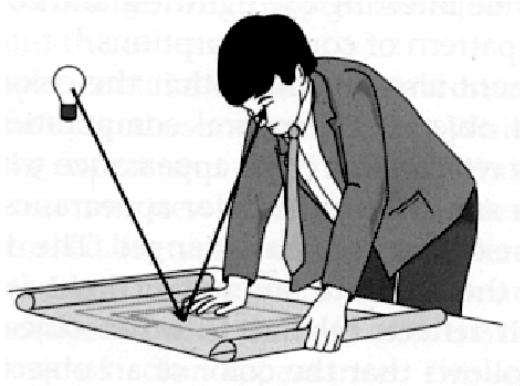


# Spectral Albedo

Ratio of incoming to outgoing radiation at different wavelengths.

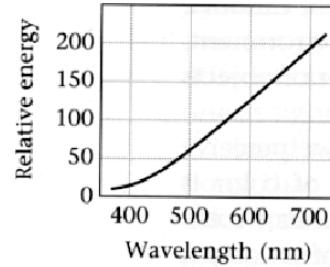


# Spectral Radiance



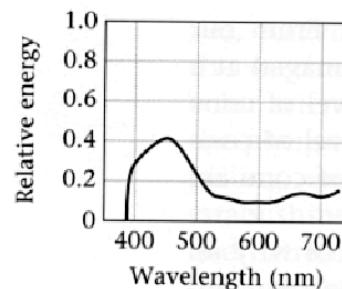
Often are more interested in relative spectral composition than in overall intensity, so the spectral BRDF computation simplifies to a wavelength-by-wavelength multiplication of relative energies.

## Spectral Irradiance



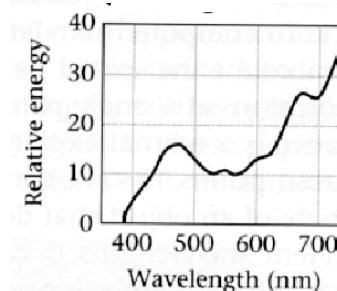
• \*

## Spectral Albedo

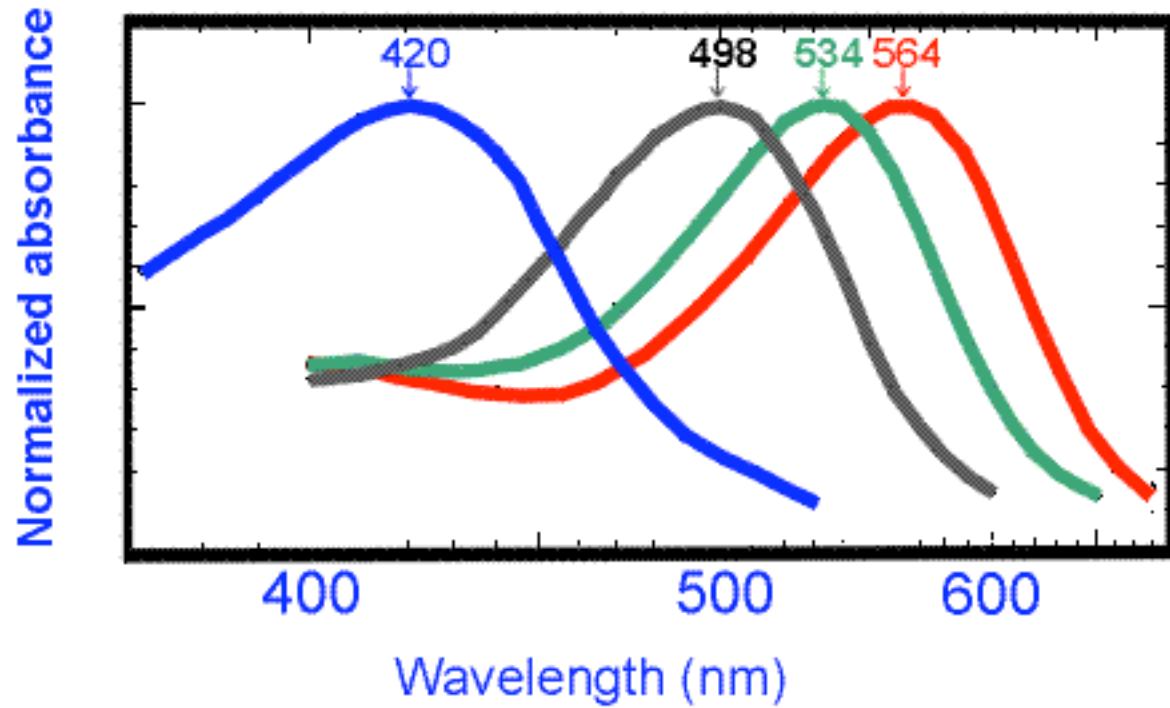
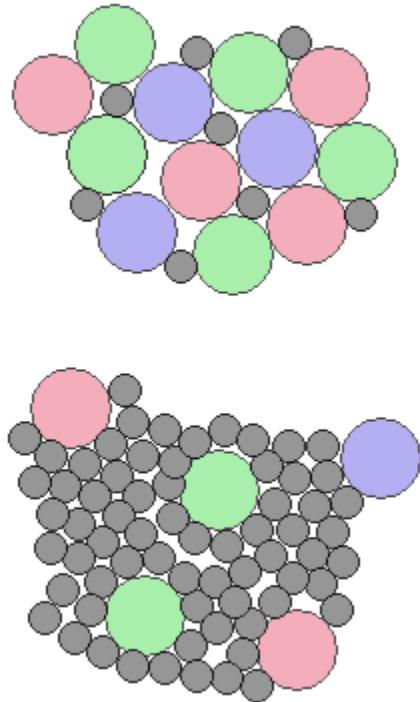


=

## Spectral Radiance



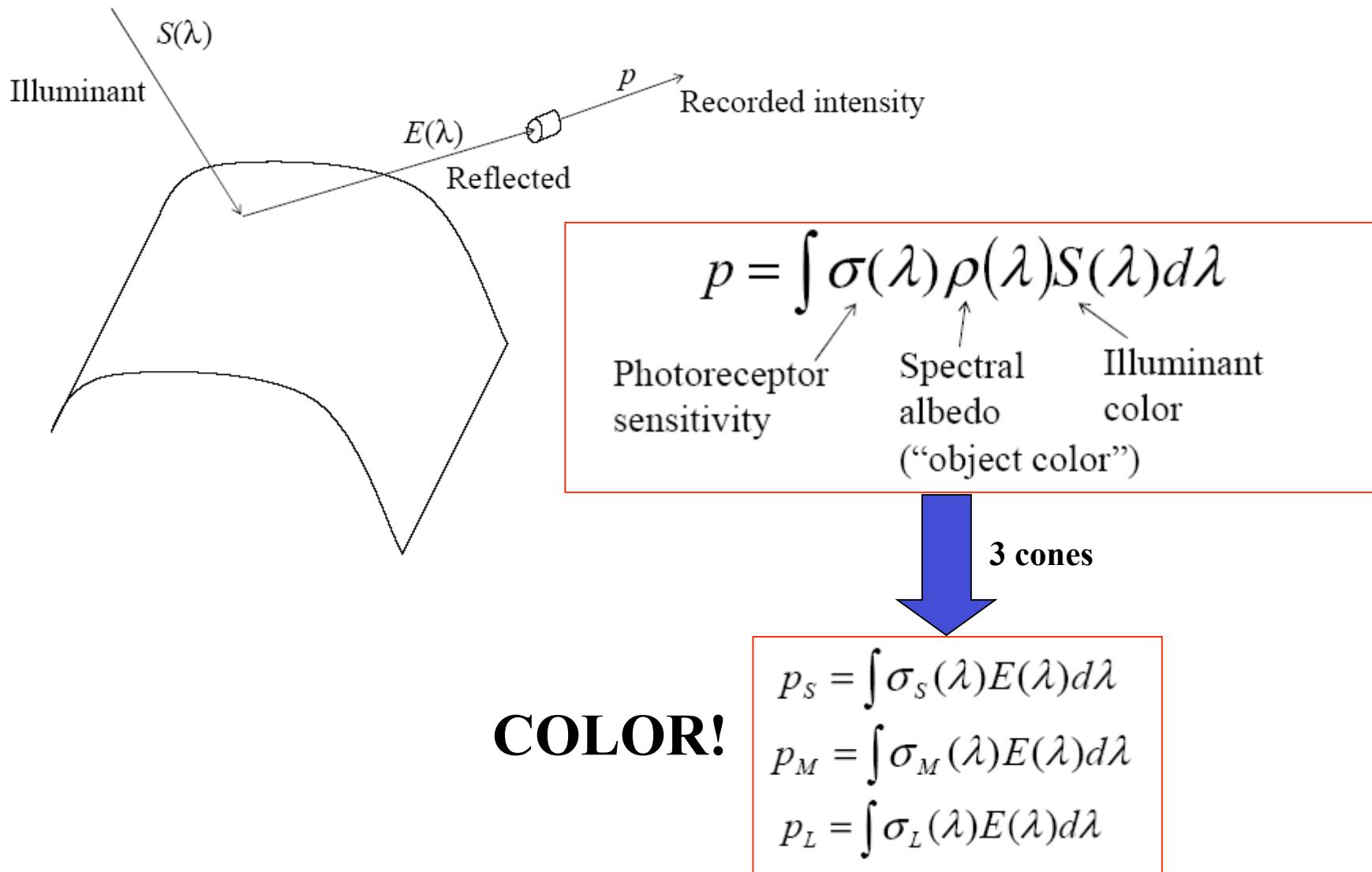
# Human Eye: Rods and Cones



After Bowmaker & Dartnall, 1980

- rods (overall intensity)
- S cones (blue)
- M cones (green)
- L cones (red)

# Putting it all Together = Color



# Describing Color

**Today we consider a sample material, human skin, and look at two approaches to describe the color of skin in order to find it in images.**

- 1) physics-based approach**
- 2) learning-based approach**

# Goal: Label Skin Pixels in an Image



## Applications:

Person finding/tracking  
Gesture recognition

# The Physics of Skin Color

## Analytic derivation:

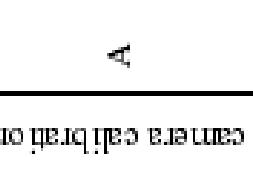
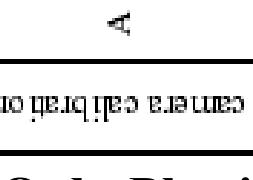
Moritz Storrung, Hans Andersen and Eric Granum, “Skin Colour Detection under Changing Lighting Conditions,” 7th Symposium on Intelligent Robotics Systems, Coimbra Portugal, July 1999.

## Experimental measurement:

Birgitta Martinkauppi, “Face Colour Under Varying Illumination: Analysis and Applications,” Ph.D. Thesis, Oulu University Press, Oulu Finland, 2002.

# Problem: Color Variation

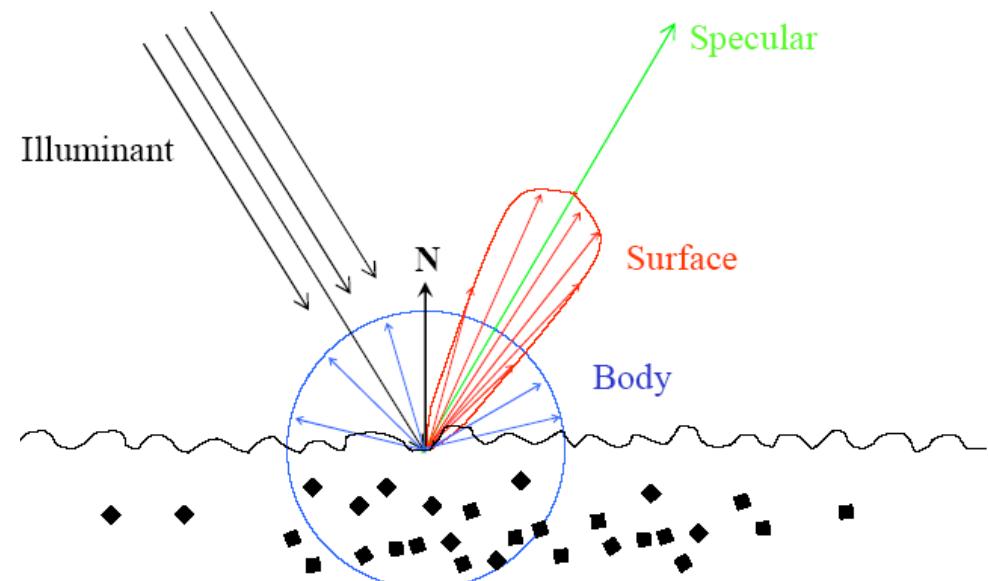
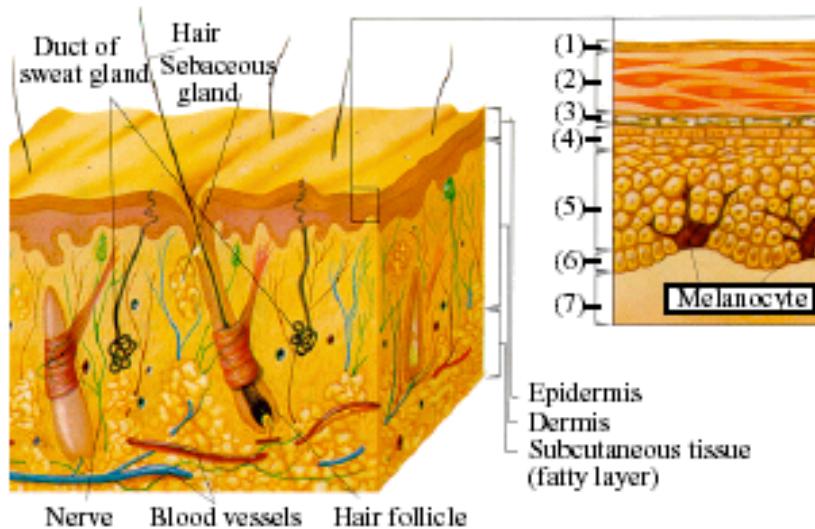
Apparent color varies due to lighting color and camera spectral response.

Current illumination		H	A	TL84	D65
Illuminant	H				
					
		H	A	TL84	D65
Reference illuminant for camera calibration					

Sample from Oulu Physics-Based Face Database

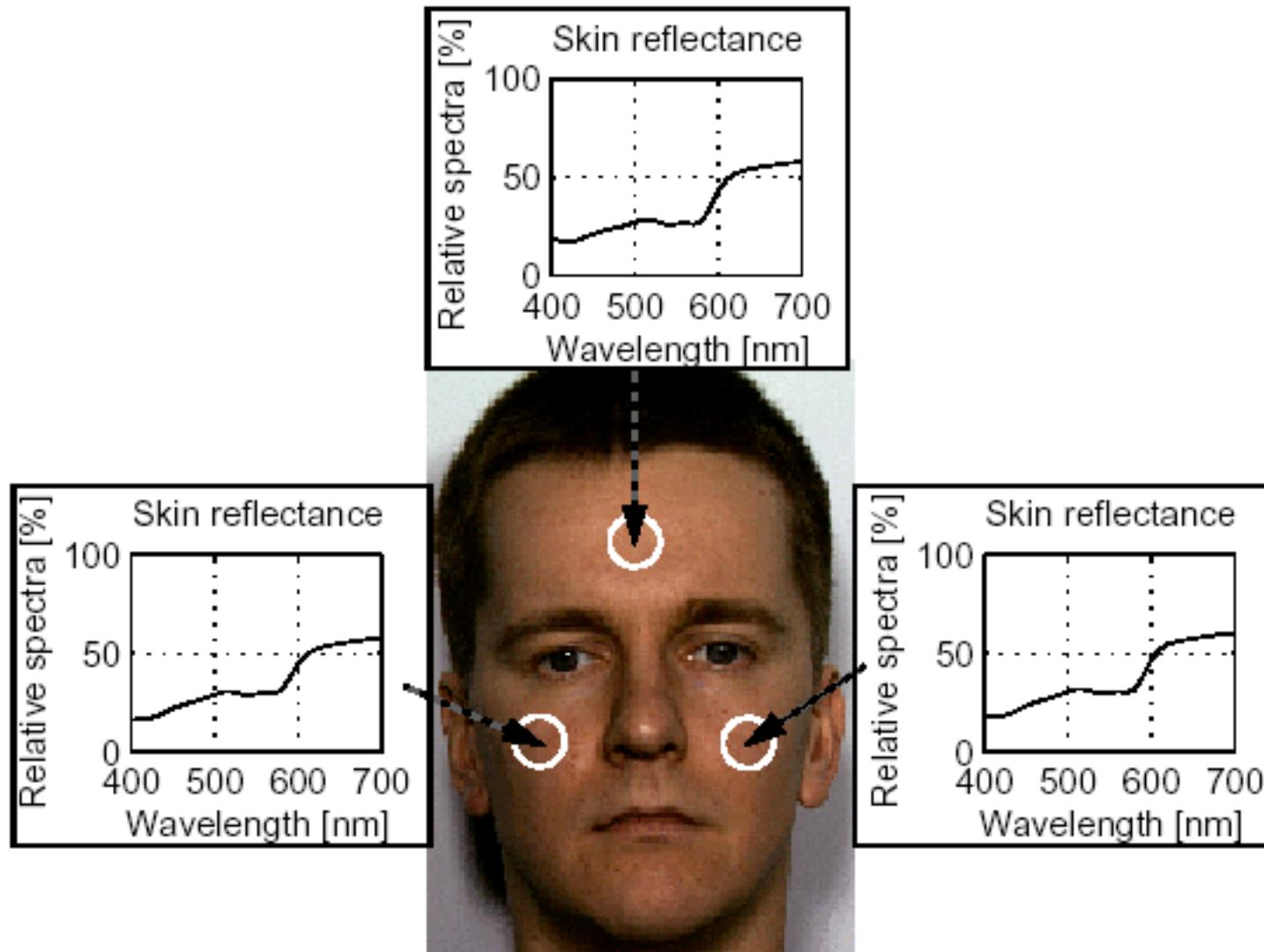
# Skin Reflectance Model

**Skin is well-modeled by a dichromatic reflectance model.**  
**transparent medium (dermis)**  
**pigmentations (hemoglobin, melanin)**  
**specular reflection (oil on skin)**

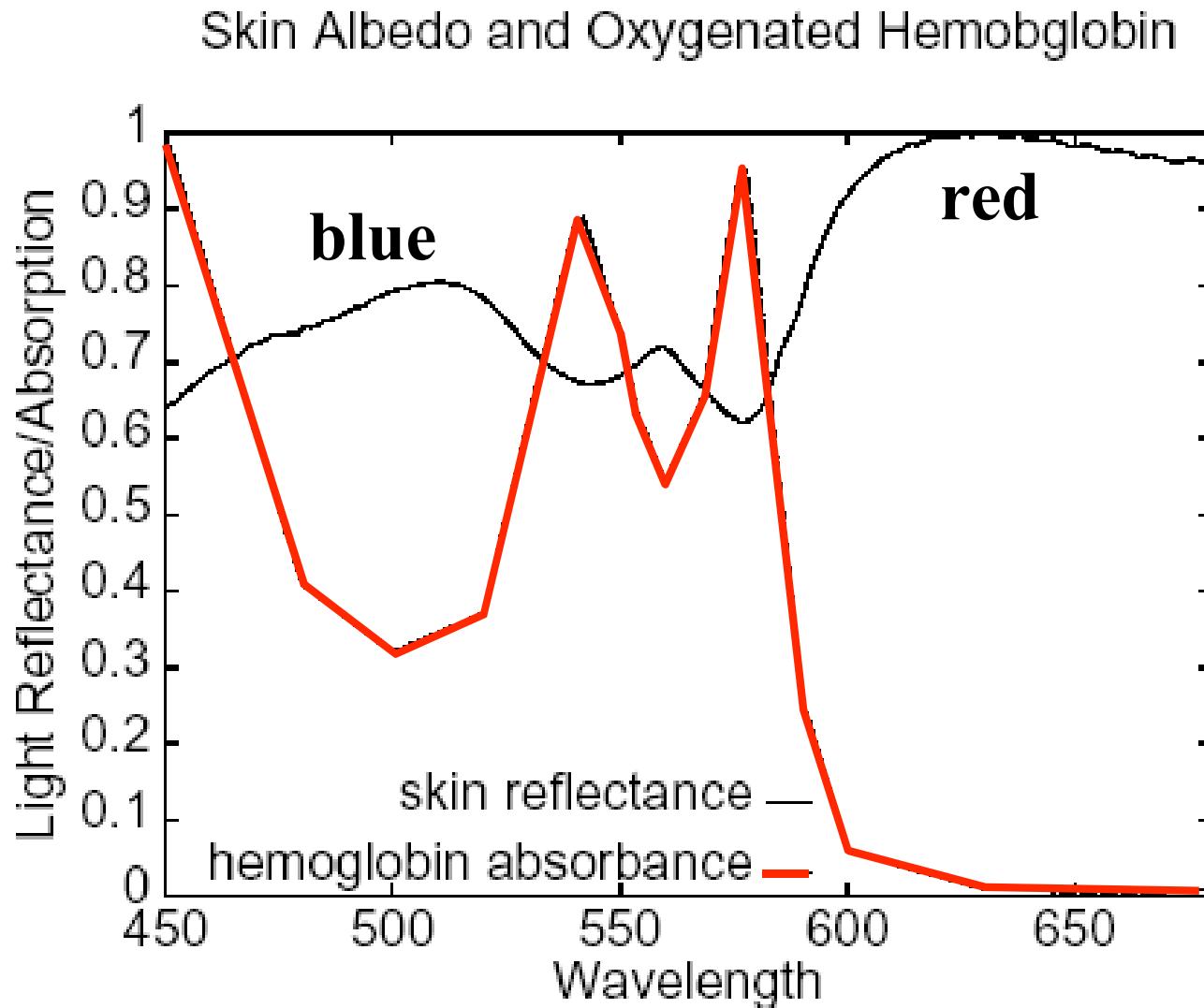


**Dichromatic reflectance model**

# Measuring Spectral Albedo of Skin

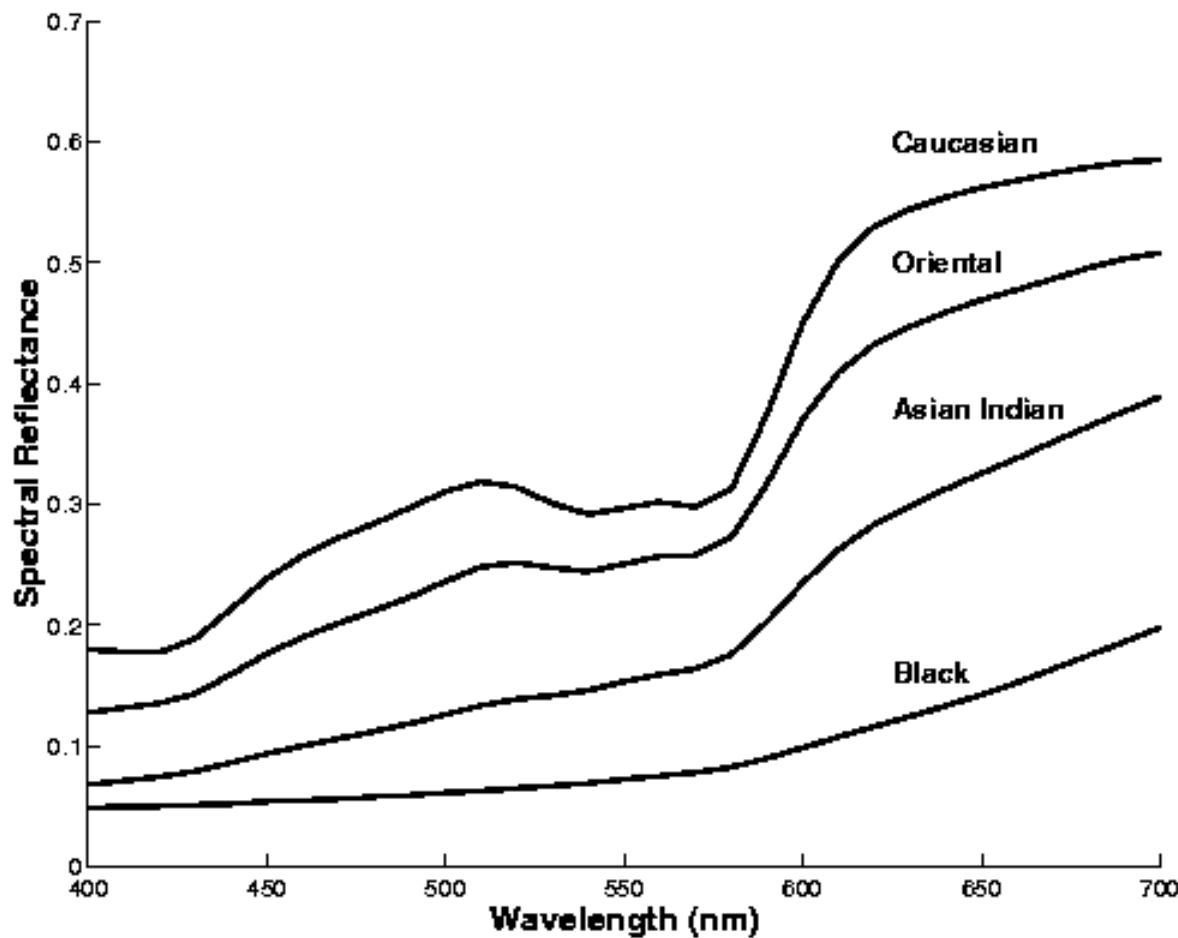


# Understanding Skin Albedo



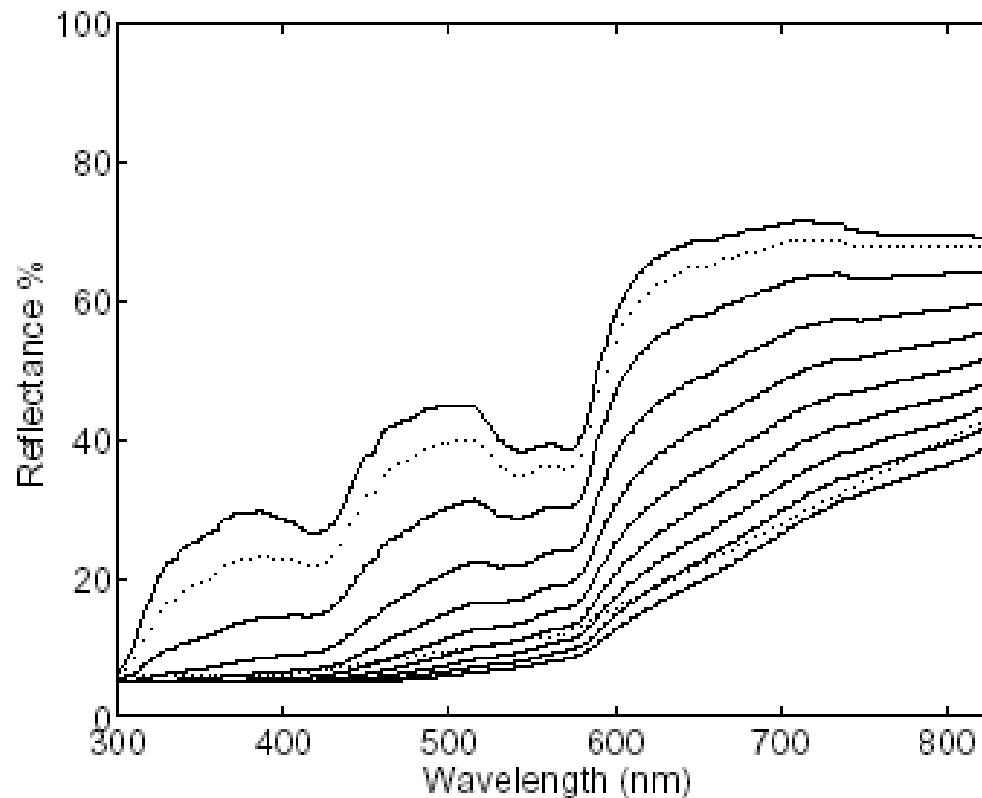
# Understanding Skin Albedo

Increase in melanin yields darker skin, masking the absorption band pattern of the hemoglobin.



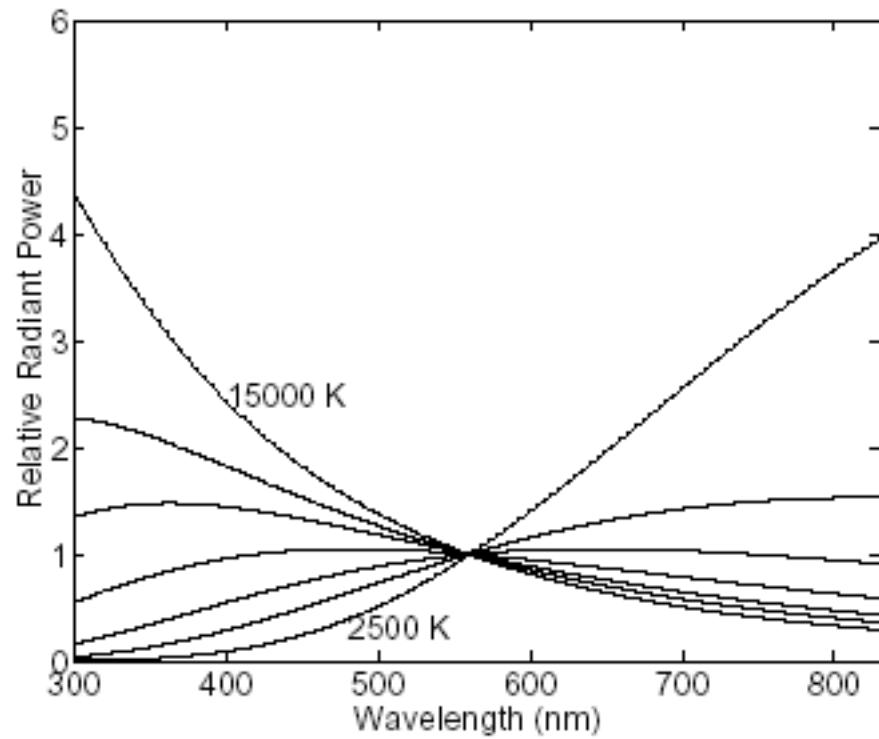
# Analytic Model

Generate different skin albedos by using observed curve for caucasian, and calculate the reduction in reflectance due to an increase in melanin (a substance that has a known absorption)

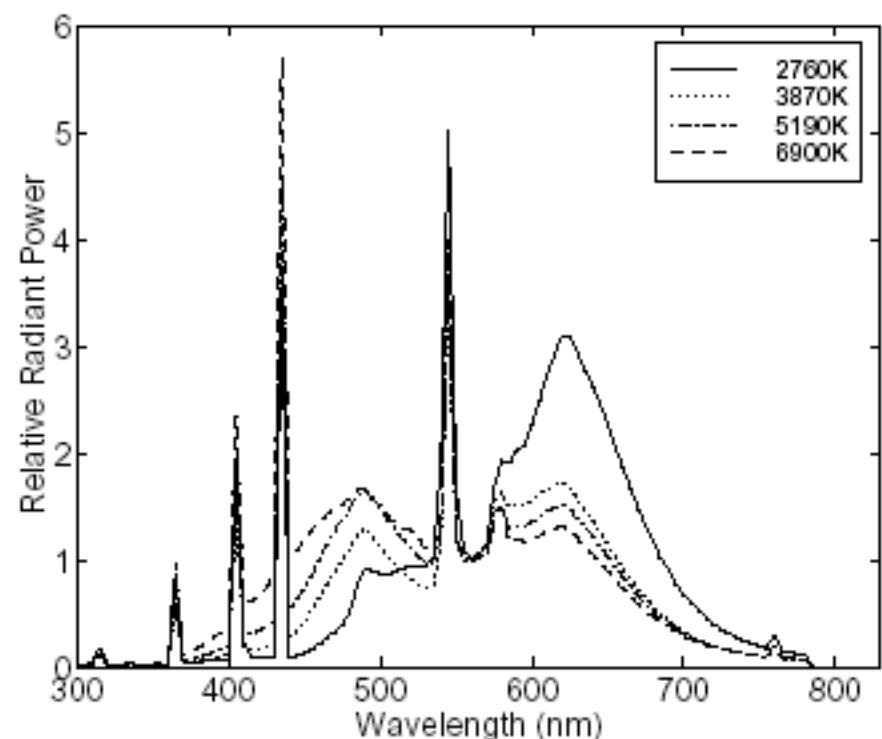


**Simpler approximation:**  $I_1(\lambda) \sim s I_2(\lambda)$  ;  $\lambda = \text{wavelength}$   
 $s = \text{scale factor}$

# Illuminant SPD

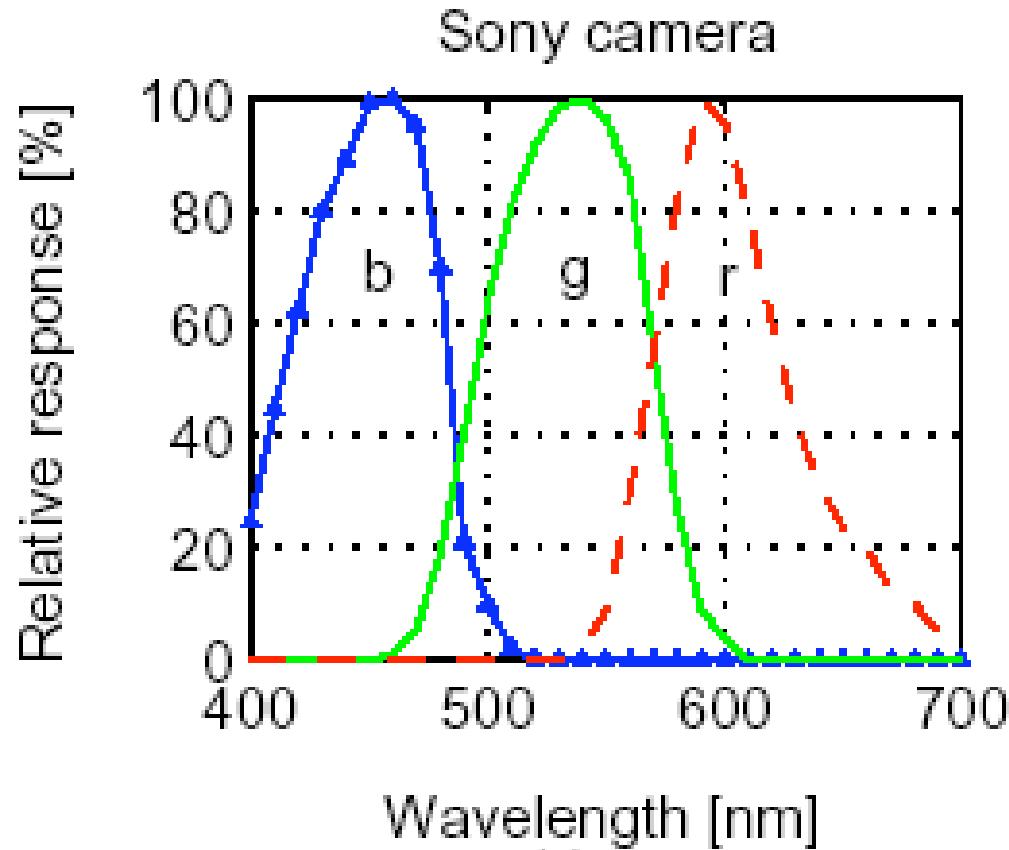


**Blackbody sources**  
(for theoretical calculations)



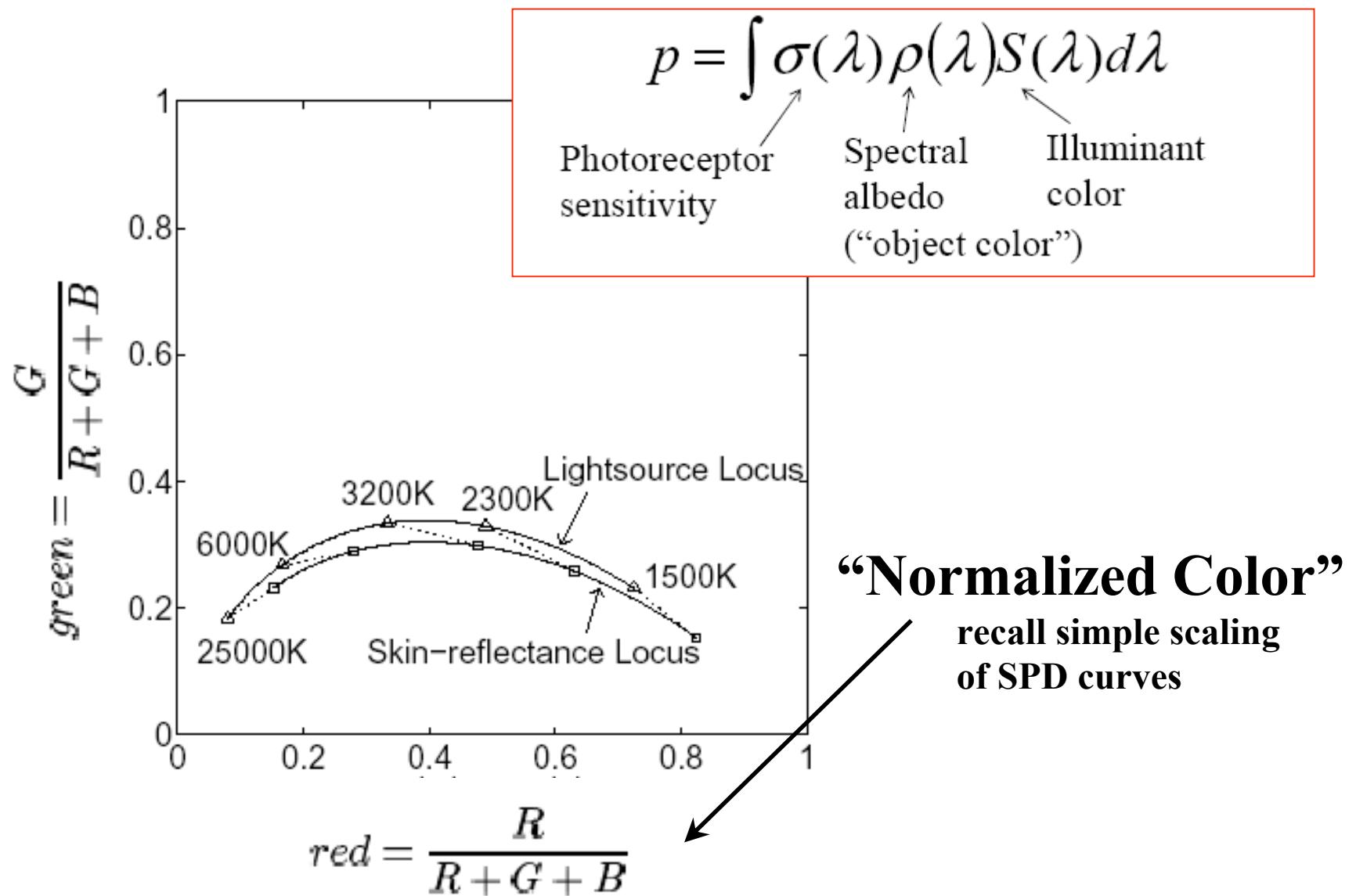
**Artificial light sources**

# Camera Spectral Response

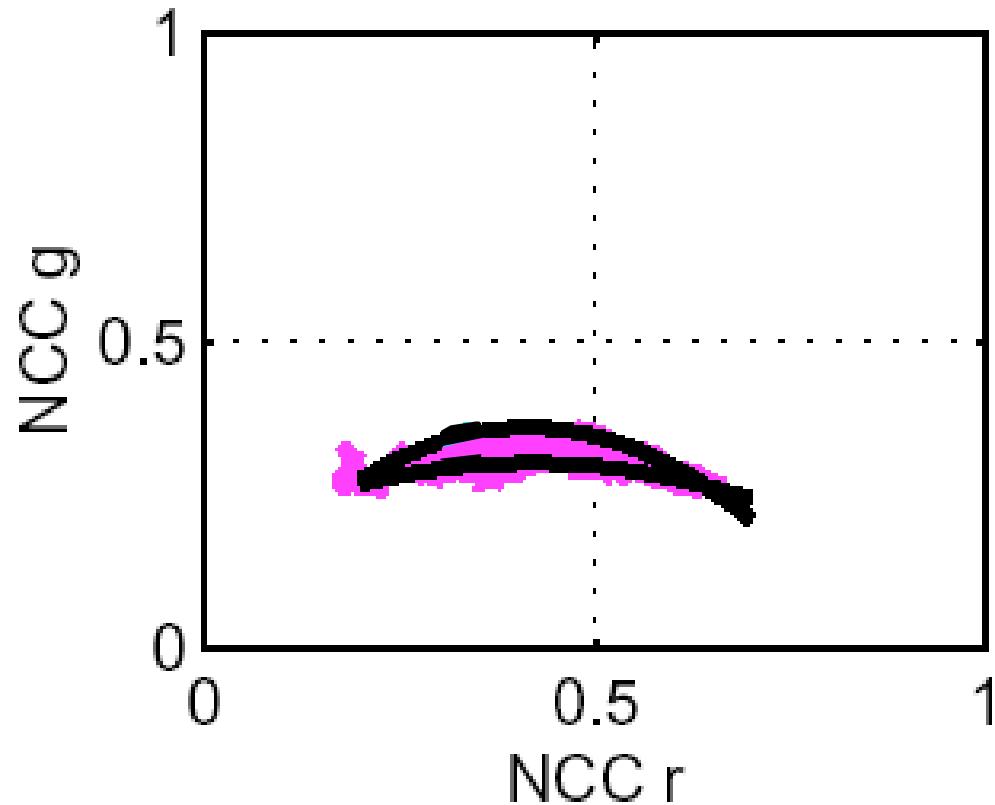


**SONY DXC-755P 3CCD**  
**(manufacturer can supply this)**

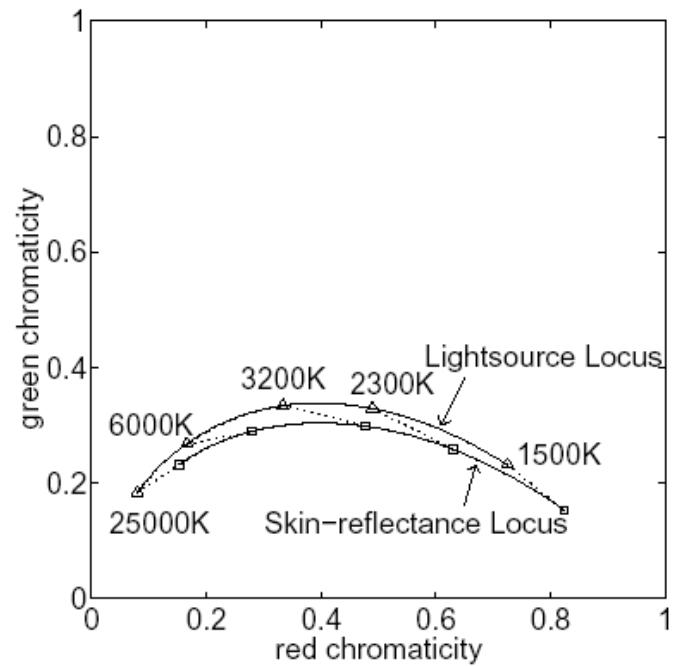
# Skin Color Locus : Analytic Computation



# Skin Color Locus : Experimental Measure

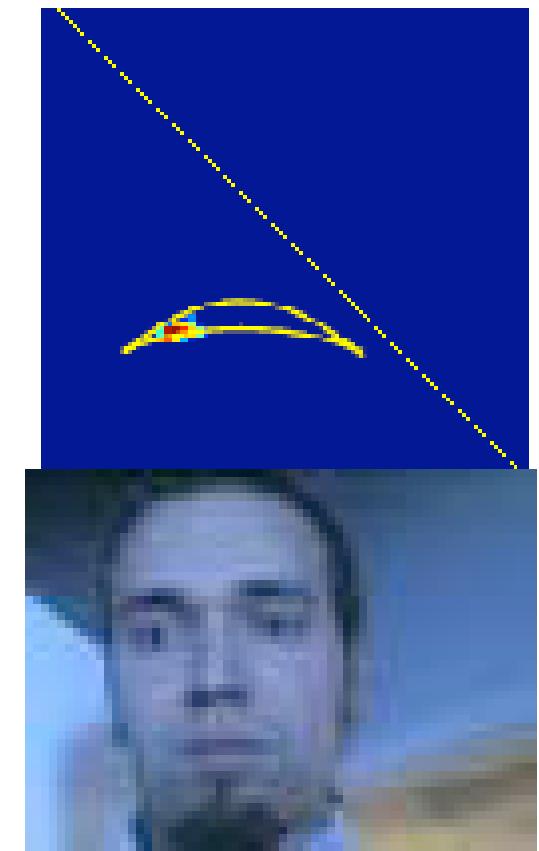
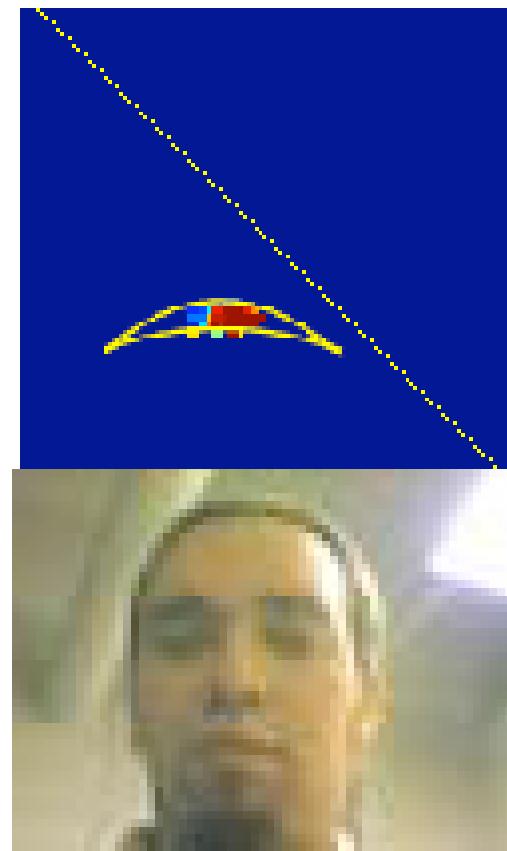
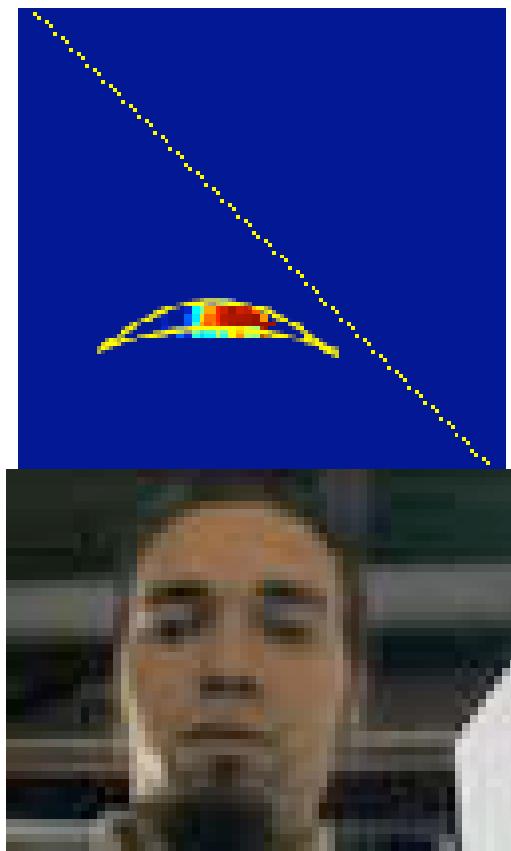


Fairly good agreement!



# Skin Locus Examples

Histograms of skin color for different lighting conditions. Red: high values, blue: low values.



# Tighter Bounds

If you know the camera and light source, you can derive much tighter analytic bounds on skin color.

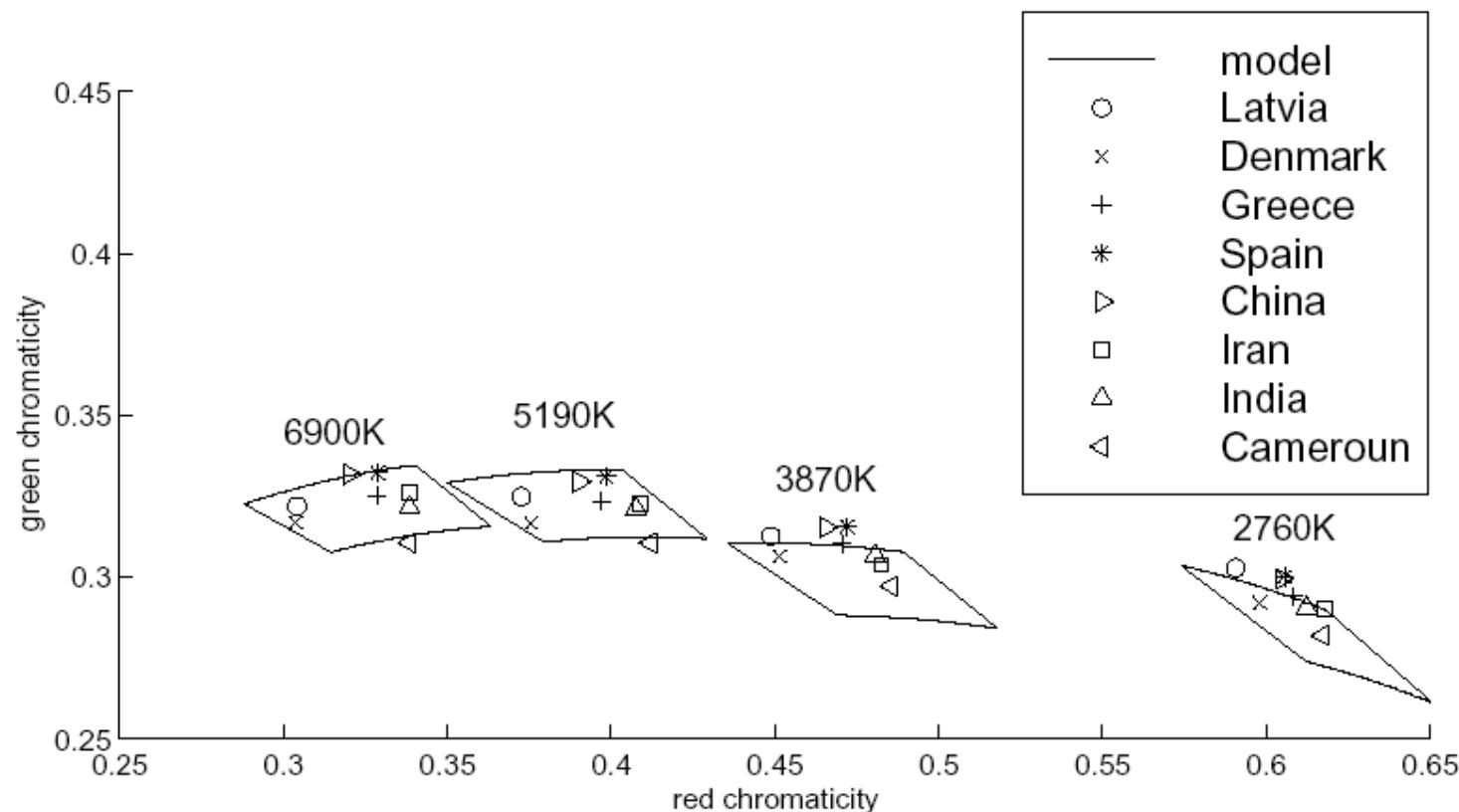
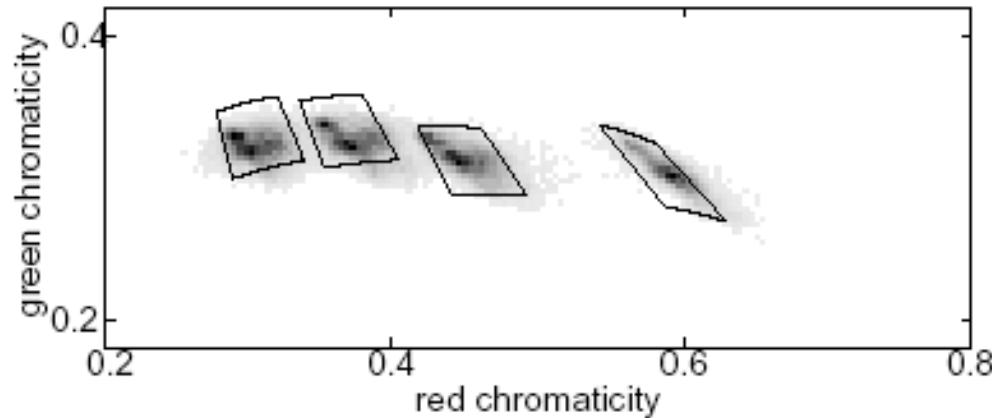


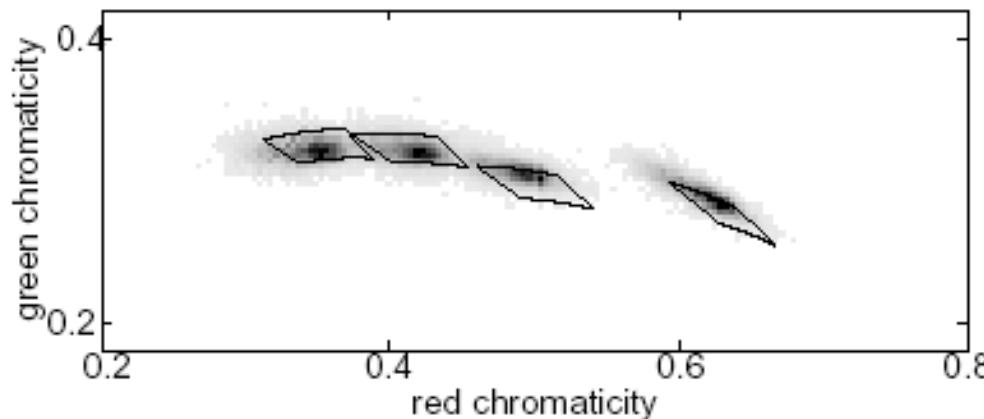
Fig.6.: Chromaticity plane with modelled skin colour areas and mean values of the measured skin colour distribution under the four different CCT as described in section 3.

# Example

Same individual under different lighting conditions.



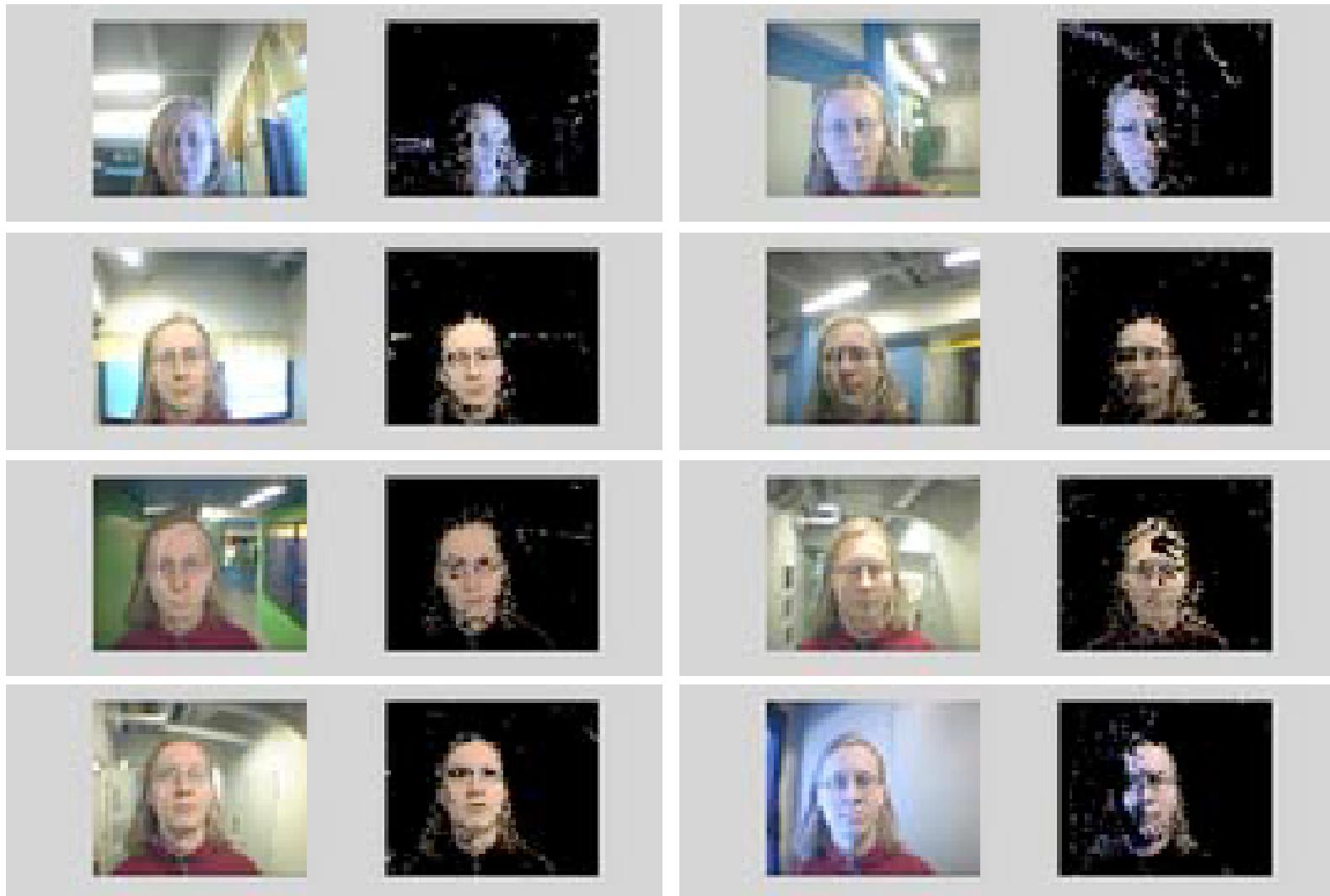
**Subject 1:**  
**Caucasian**



**Subject 2:**  
**Asian Indian**

# Sample Application

Face tracking under varying illumination conditions



# Jones and Rehg, 2002

**“Statistical Color Models with Application to Skin Detection”, M. J. Jones and J. M. Rehg,  
*Int. J. of Computer Vision*, 46(1):81-96, Jan 2002**

## General Idea:

- Drop the physics. Learn from examples instead.
- Learn distributions of skin and nonskin color
- Nonparametric distributions: color histograms
- Bayesian classification of skin pixels

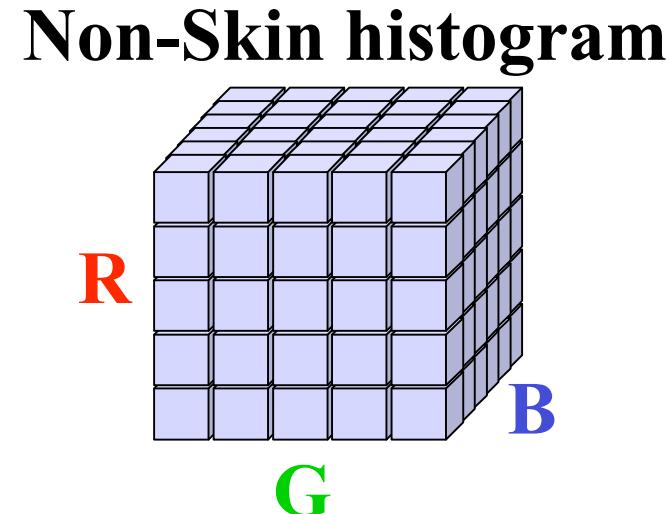
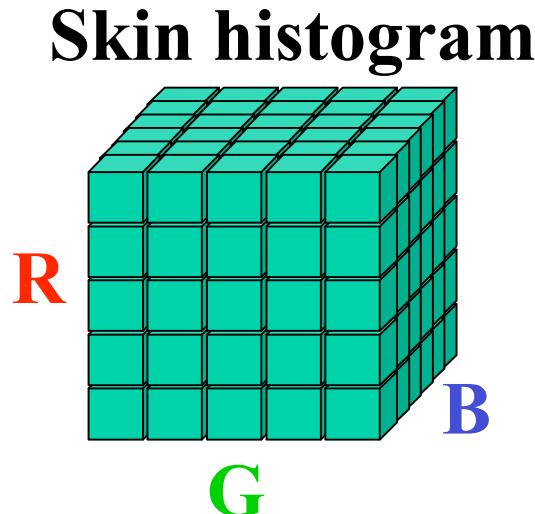
# Learning from Examples

First, have some poor grad student hand label thousands of images

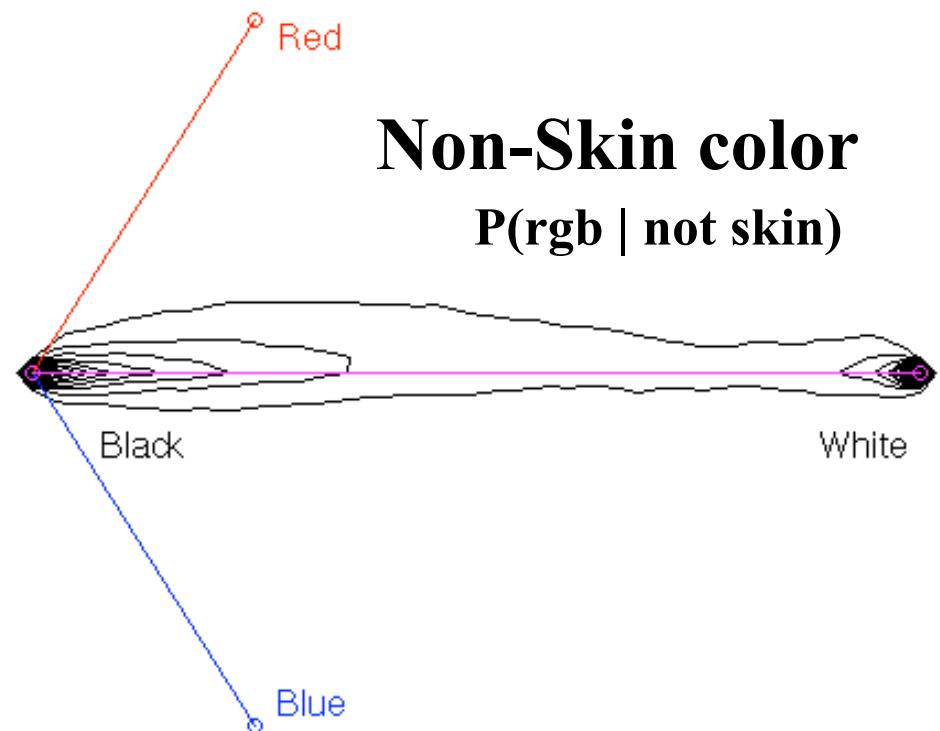
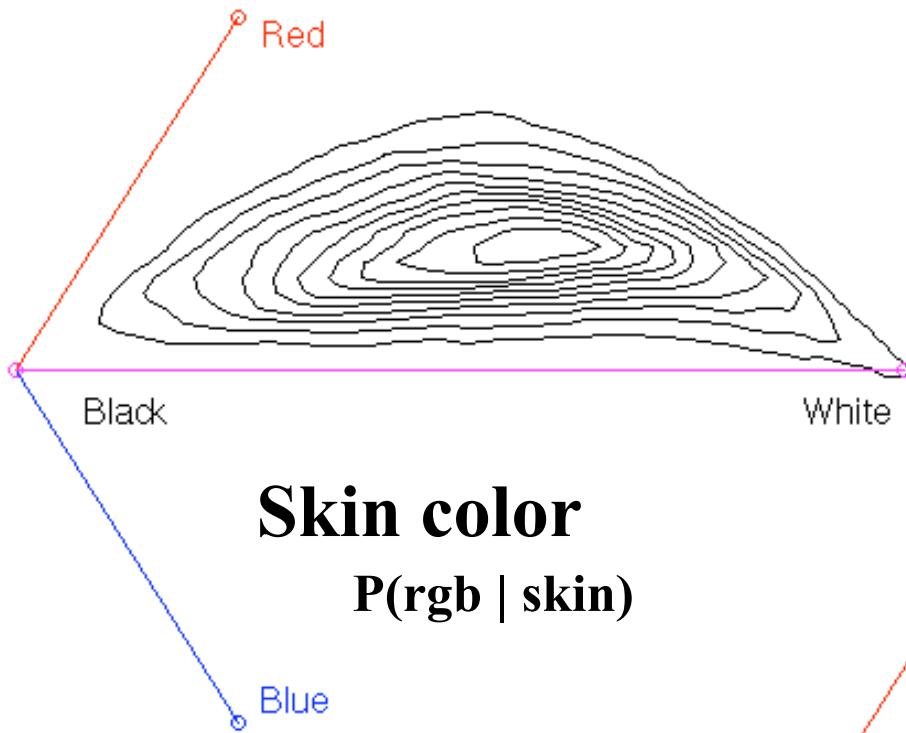
$$P(\text{rgb} \mid \text{skin}) = \frac{\text{number of times rgb seen for a skin pixel}}{\text{total number of skin pixels seen}}$$

$$P(\text{rgb} \mid \text{not skin}) = \frac{\text{number of times rgb seen for a non-skin pixel}}{\text{total number of non-skin pixels seen}}$$

These statistics stored in two 32x32x32 RGB histograms



# Learned Distributions



# Likelihood Ratio

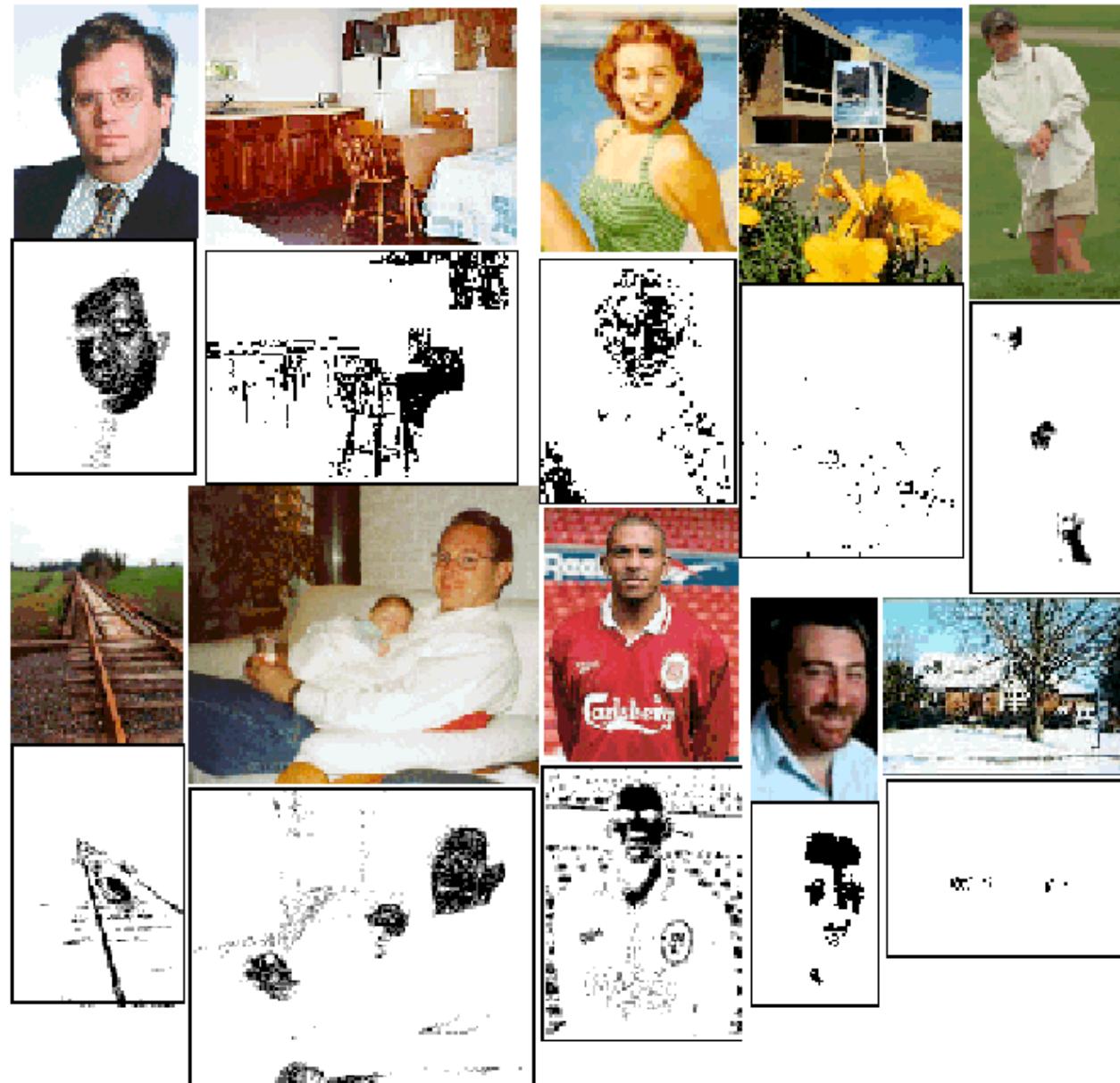
Label a pixel skin if  $\frac{P(\text{rgb} \mid \text{skin})}{P(\text{rgb} \mid \text{not skin})} > \Theta$

$$\Theta = \frac{\text{(cost of false positive)} P(\text{ seeing not skin})}{\text{(cost of false negative)} P(\text{ seeing skin})}$$

$$0 \leq \Theta \leq 1$$

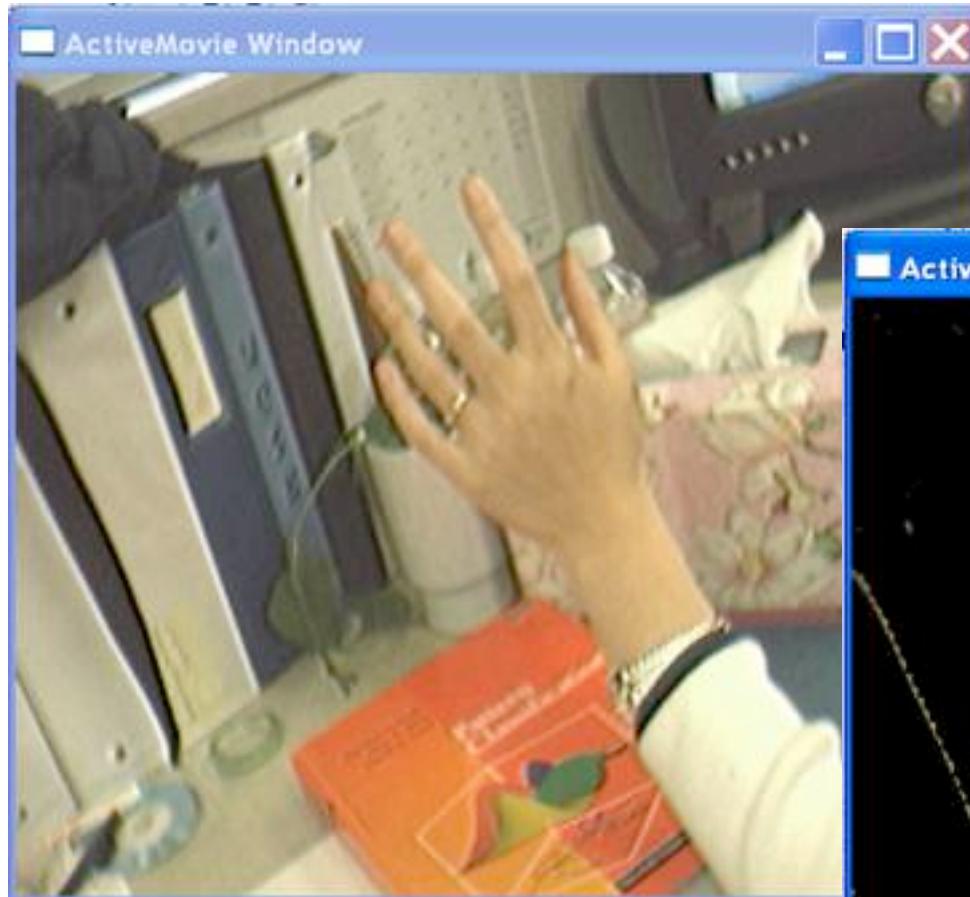
# Sample Pixel Classifications

$$\Theta = .4$$



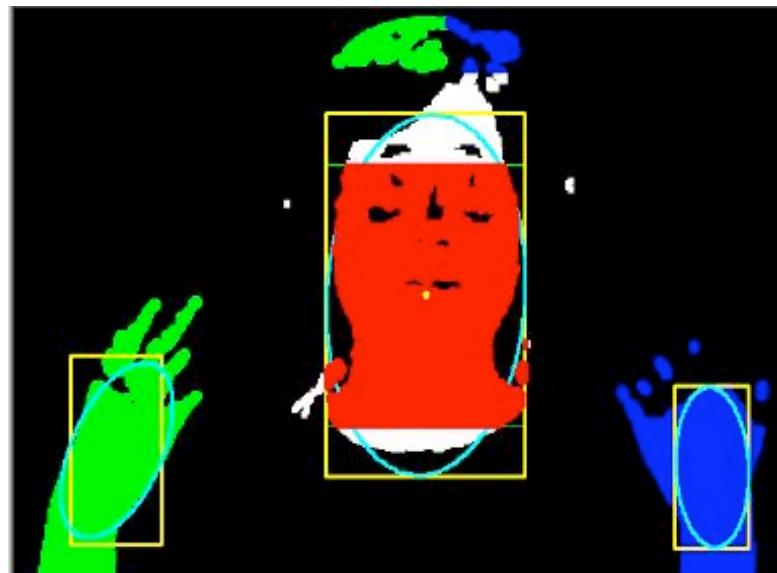
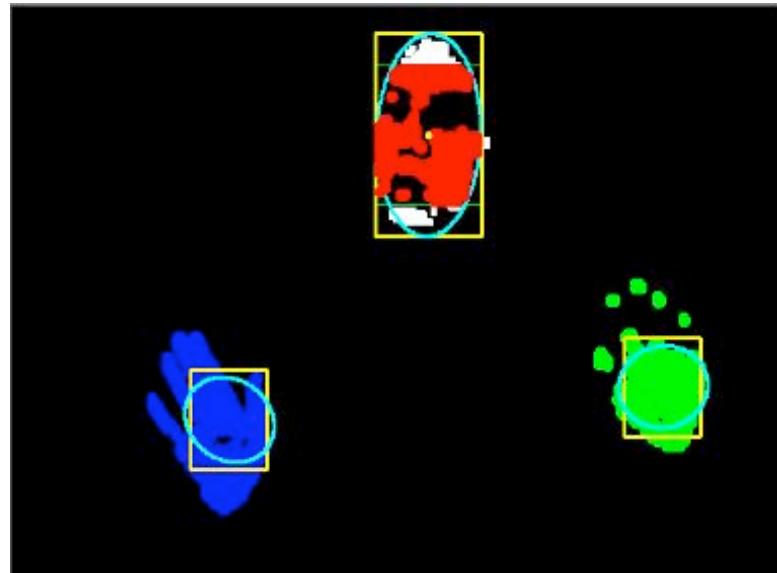
# Sample Application: HCI

Haiying Guan, Matthew  
Turk, UCSB

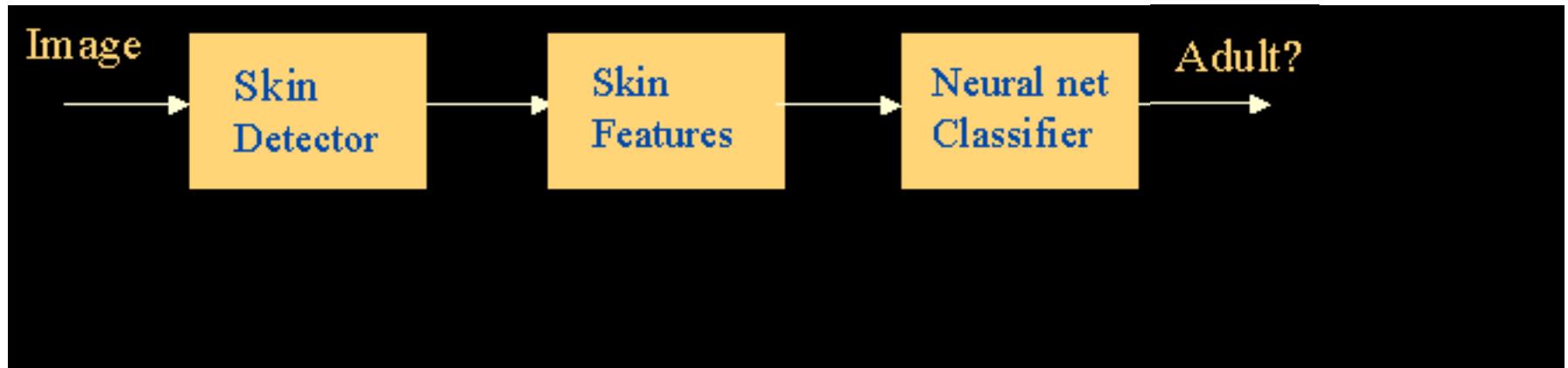


# Sample Application: HCI

Haiying Guan, Matthew Turk, UCSB



# Sample Use: Adult Image Classification

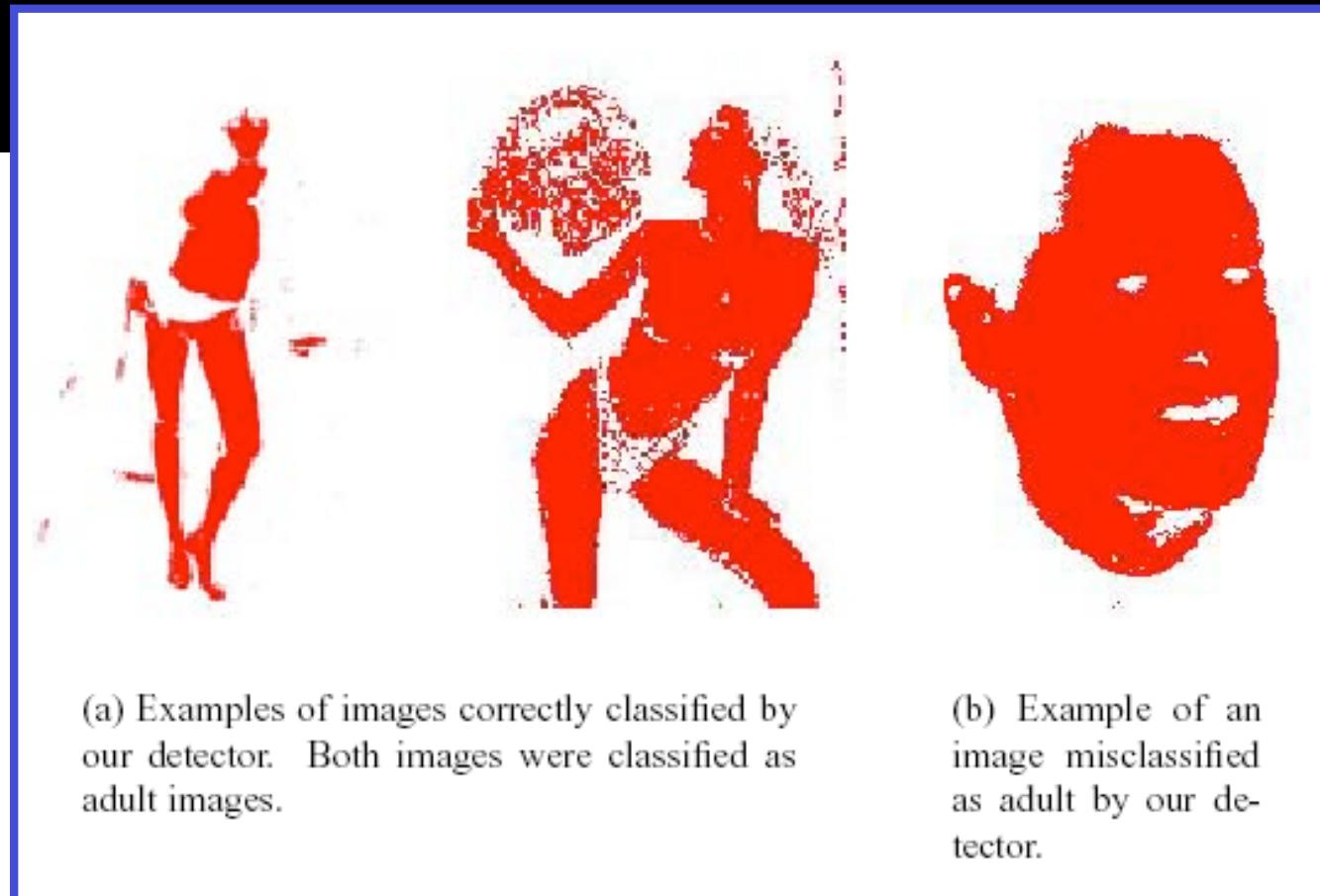


## Based on Five Features:

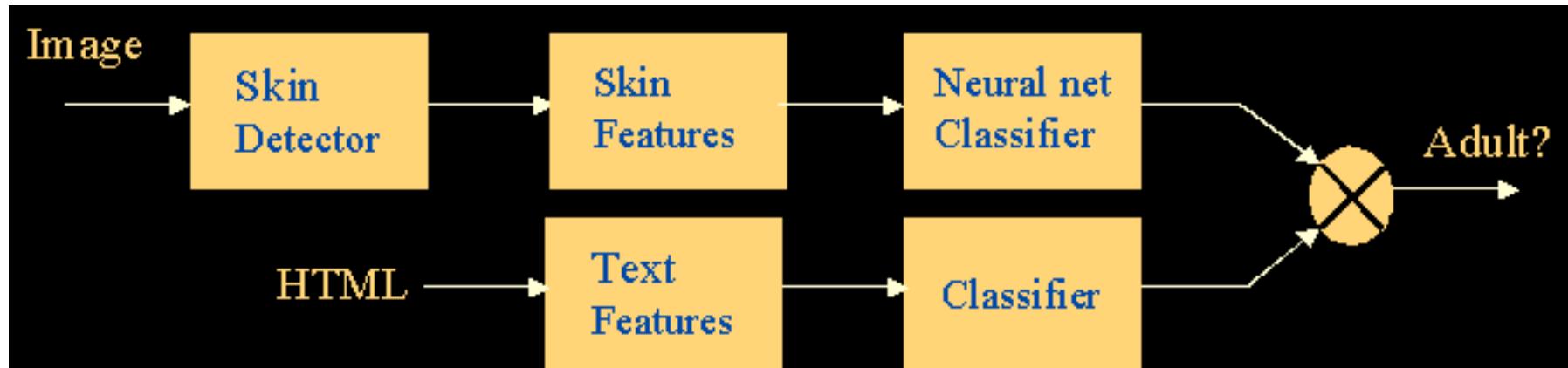
- Percentage of pixels detected as skin.
- Average probability of the skin pixels.
- Size in pixels of the largest connected component of skin.
- Number of connected components of skin.
- Percentage of colors with no entries in the skin and non-skin histograms

Jones and Rehg

# Adult Image Classification



# Combining Color and Text



	<i>% correctly detected adult images</i>	<i>% false alarms</i>
<i>Color-based Detector</i>	85.8%	7.5%
<i>Text-based Detector</i>	84.9%	1.1%
<i>Combined Detector</i>	93.9%	8.0%

# Adult Image Classification

## Other related work:

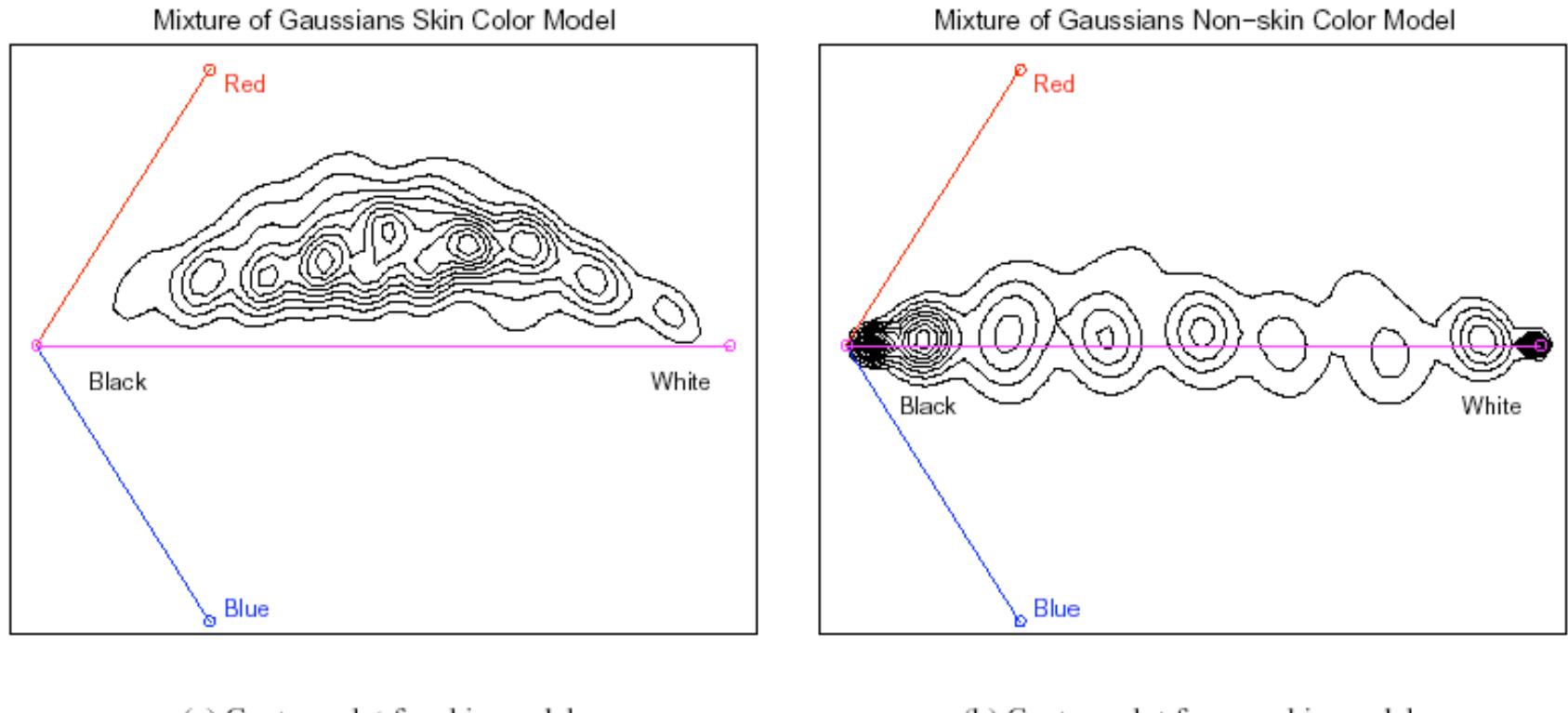
**M.M. Fleck, D.A. Forsyth and C. Bregler, “Finding Naked People,” *Proc. European Conf. on Computer Vision*, Springer-Verlag, 1996.** p. 593-602

**James Wang, Jia Li, Gio Wiederhold and Oscar Firschein, “System for Screen Objectionable Images” *Computer Communications*, Vol 21(15), pp.1355-1369, Elsevier, 1998.**

# Back to Jones and Rehg Model

A compact description is provided by converting the histogram-based model into a Gaussian Mixture model.

$$P(\mathbf{x}) = \sum_{i=1}^N w_i \frac{1}{(2\pi)^{\frac{3}{2}} |\Sigma_i|^{\frac{1}{2}}} e^{-\frac{1}{2}(\mathbf{x}-\mu_i)^T \Sigma_i^{-1} (\mathbf{x}-\mu_i)},$$



# Jones and Rehg Mixture Model

Mixture of Gaussian Skin Color Model

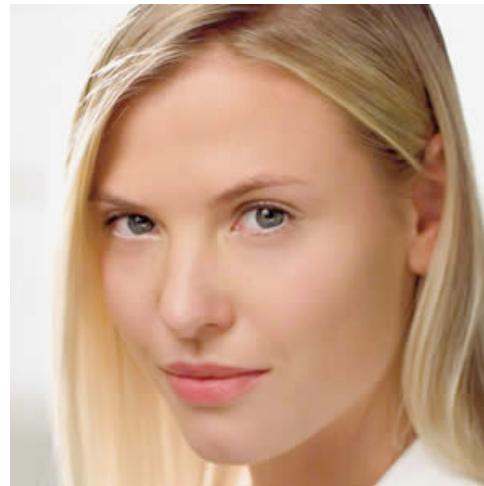
<i>Kernel</i>	<i>Mean</i>	<i>Covariance</i>	<i>Weight</i>
1	(73.53, 29.94, 17.76)	(765.40, 121.44, 112.80)	0.0294
2	(249.71, 233.94, 217.49)	(39.94, 154.44, 396.05)	0.0331
3	(161.68, 116.25, 96.95)	(291.03, 60.48, 162.85)	0.0654
4	(186.07, 136.62, 114.40)	(274.95, 64.60, 198.27)	0.0756
5	(189.26, 98.37, 51.18)	(633.18, 222.40, 250.69)	0.0554
6	(247.00, 152.20, 90.84)	(65.23, 691.53, 609.92)	0.0314
7	(150.10, 72.66, 37.76)	(408.63, 200.77, 257.57)	0.0454
8	(206.85, 171.09, 156.34)	(530.08, 155.08, 572.79)	0.0469
9	(212.78, 152.82, 120.04)	(160.57, 84.52, 243.90)	0.0956
10	(234.87, 175.43, 138.94)	(163.80, 121.57, 279.22)	0.0763
11	(151.19, 97.74, 74.59)	(425.40, 73.56, 175.11)	0.1100
12	(120.52, 77.55, 59.82)	(330.45, 70.34, 151.82)	0.0676
13	(192.20, 119.62, 82.32)	(152.76, 92.14, 259.15)	0.0755
14	(214.29, 136.08, 87.24)	(204.90, 140.17, 270.19)	0.0500
15	(99.57, 54.33, 38.06)	(448.13, 90.18, 151.29)	0.0667
16	(238.88, 203.08, 176.91)	(178.38, 156.27, 404.99)	0.0749

# Jones and Rehg Mixture Model

## Mixture of Gaussian Non-skin Color Model

<i>Kernel</i>	<i>Mean</i>	<i>Covariance</i>	<i>Weight</i>
1	(254.37, 254.41, 253.82)	(2.77, 2.81, 5.46)	0.0637
2	(9.39, 8.09, 8.52)	(46.84, 33.59, 32.48)	0.0516
3	(96.57, 96.95, 91.53)	(280.69, 156.79, 436.58)	0.0864
4	(160.44, 162.49, 159.06)	(355.98, 115.89, 591.24)	0.0636
5	(74.98, 63.23, 46.33)	(414.84, 245.95, 361.27)	0.0747
6	(121.83, 60.88, 18.31)	(2502.24, 1383.53, 237.18)	0.0365
7	(202.18, 154.88, 91.04)	(957.42, 1766.94, 1582.52)	0.0349
8	(193.06, 201.93, 206.55)	(562.88, 190.23, 447.28)	0.0649
9	(51.88, 57.14, 61.55)	(344.11, 191.77, 433.40)	0.0656
10	(30.88, 26.84, 25.32)	(222.07, 118.65, 182.41)	0.1189
11	(44.97, 85.96, 131.95)	(651.32, 840.52, 963.67)	0.0362
12	(236.02, 236.27, 230.70)	(225.03, 117.29, 331.95)	0.0849
13	(207.86, 191.20, 164.12)	(494.04, 237.69, 533.52)	0.0368
14	(99.83, 148.11, 188.17)	(955.88, 654.95, 916.70)	0.0389
15	(135.06, 131.92, 123.10)	(350.35, 130.30, 388.43)	0.0943
16	(135.96, 103.89, 66.88)	(806.44, 642.20, 350.36)	0.0477

# Homework: Due Friday Dec 7



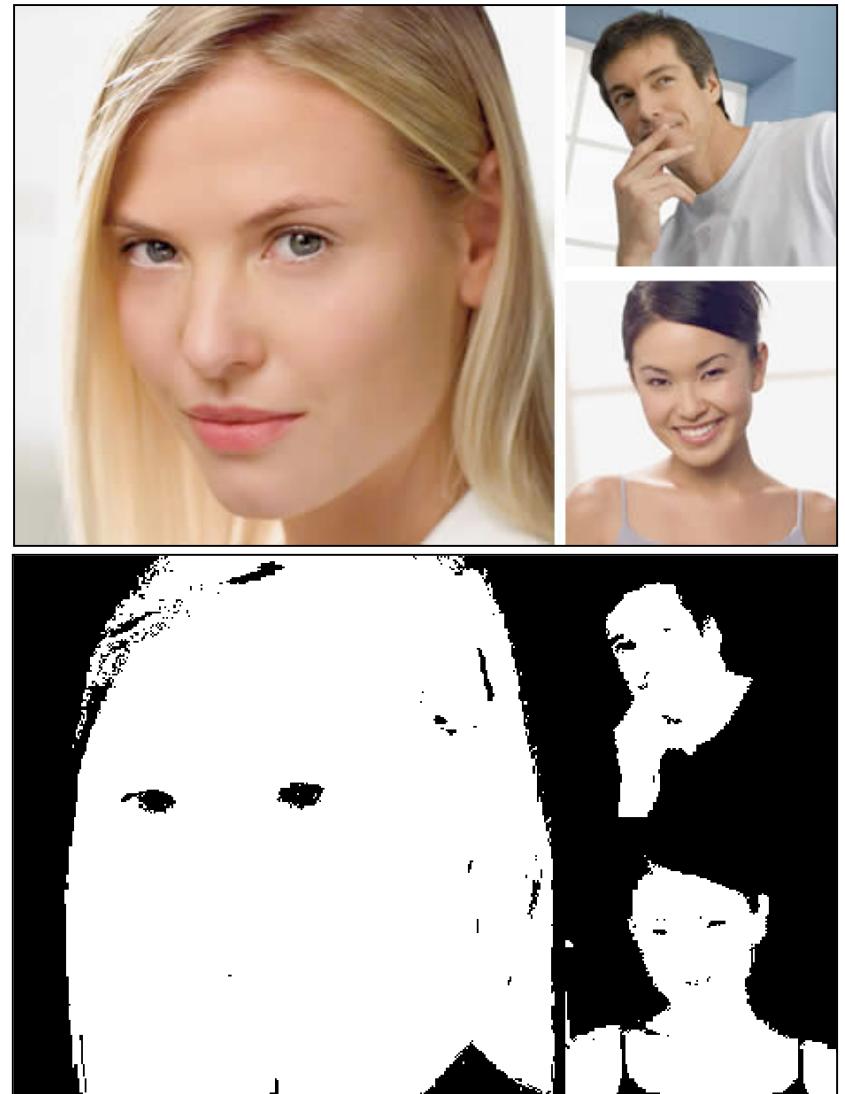
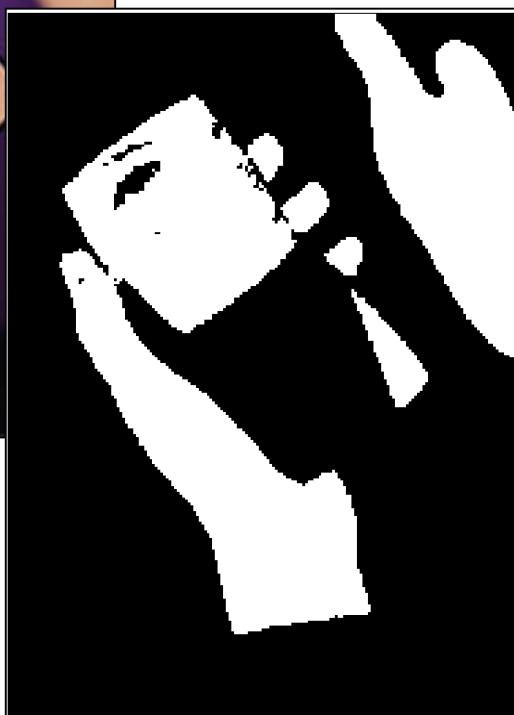
- Download jrmogskin.m from the course web site
- Try it on your own images!

# What to Hand In

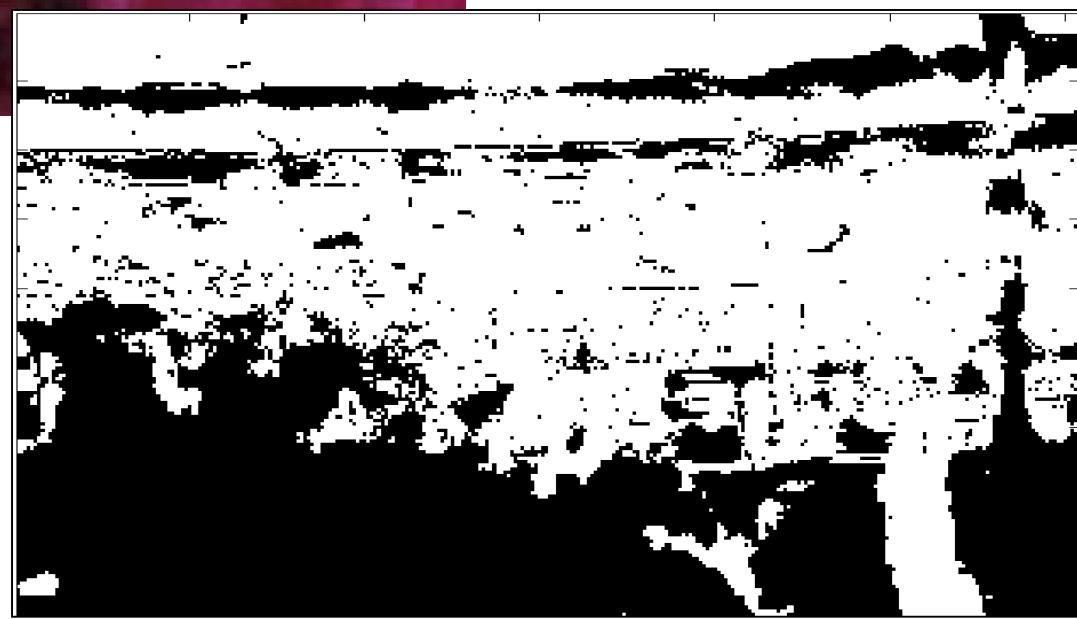
A short report, in Angel:

- 1) one example where it works wonderfully well
- 2) one example showing false positives (things that are not skin, but that are labeled as skin).
- 3) one example showing false negatives (a patch of skin that is not labeled), along with an educated guess about why it was missed.

# Examples Working Well



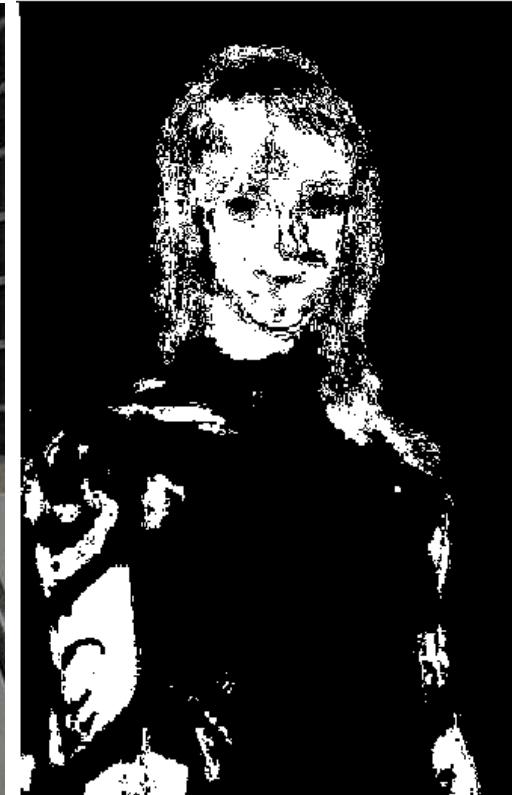
# Example of False Positives



# Examples

## Example of False Negatives

**Explanation:**  
**paint on skin**  
**changes the**  
**spectral albedo**



# Important Constraint

**No X-rated images!!!! Keep it clean  
for the report.**