Segmentation d'Images Couleurs et Multispectrales de la Peau

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Overview

- **Motivation:**

  Detection of Melanoma with Computer-Aided Diagnosis System;

- **Methodology:**

  Graph-cut Based Image Segmentation Framework with “Soft” Classification and Multiple Visual Features;

- **Applications:**

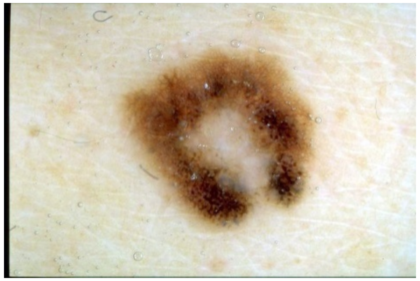
  Segmentation of Melanoma:

  - **Skin Chromophore Extraction**
  - **Automatic PSLs Segmentation (APS) Framework**

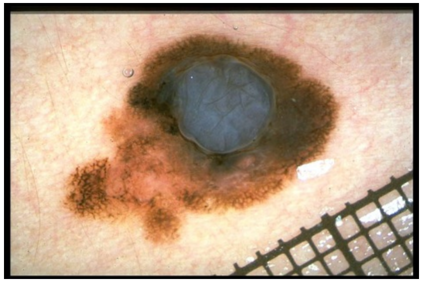
- **Conclusion and Perspectives.**

What is melanoma and why early diagnosis vital ?

Melanoma is the deadliest type of skin cancer.

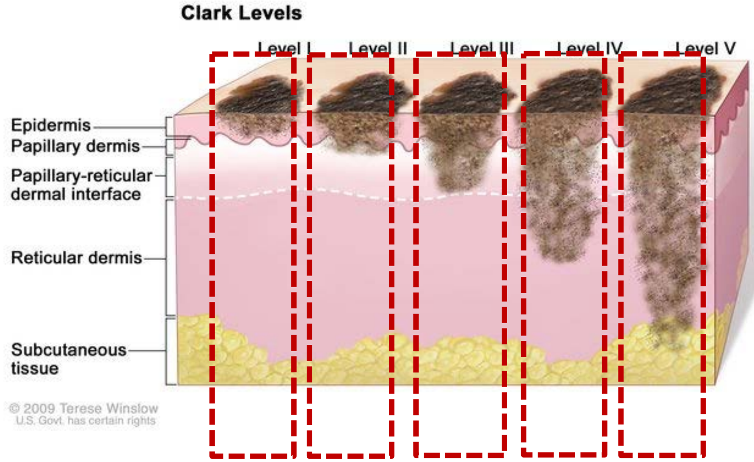


Melanoma *in situ*
(malignant)



Invasive Melanoma
(malignant)

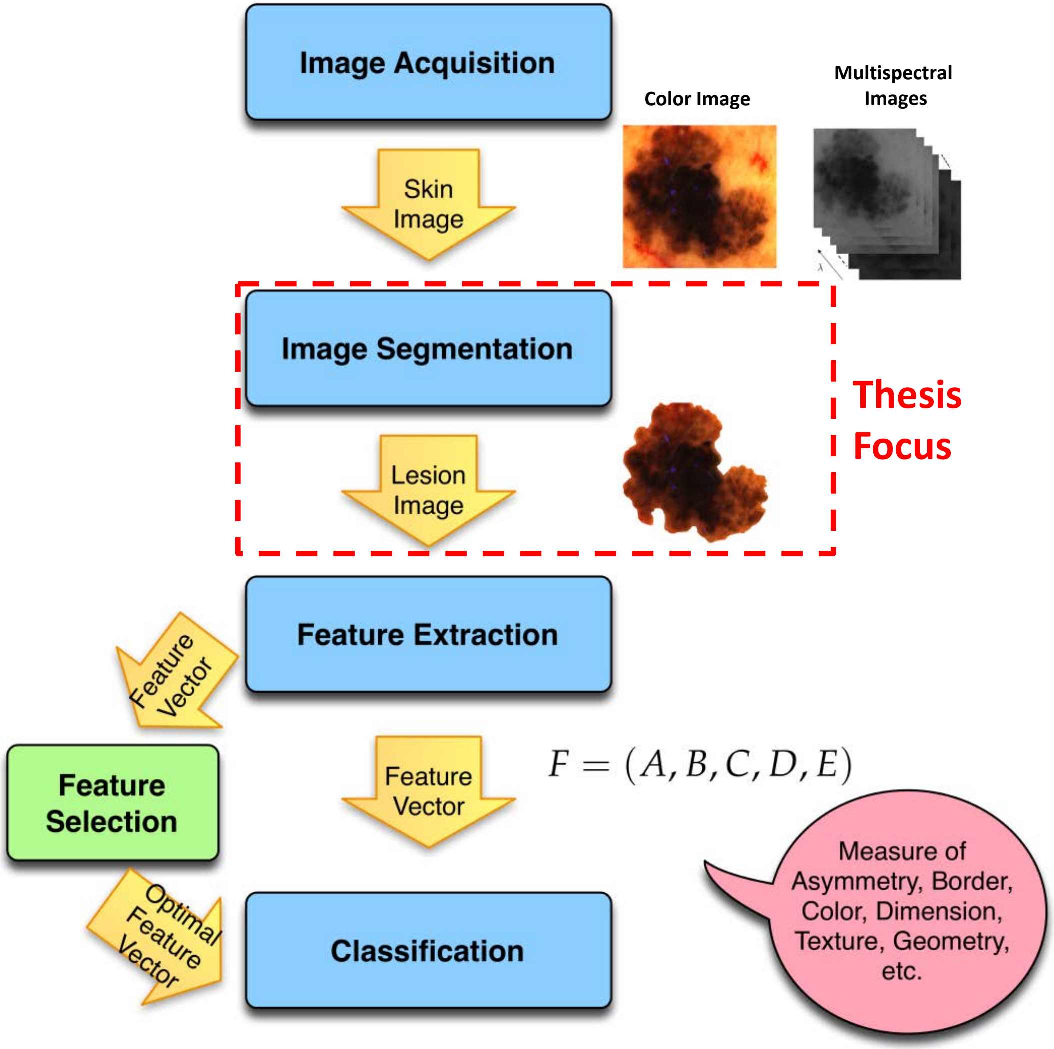
✓ Prognostic Analysis: Clark Levels



Survive Rate: 100% 90% 80% 50% 20%

How to diagnose?

✓ **Computer-Aided Diagnosis (CAD)**



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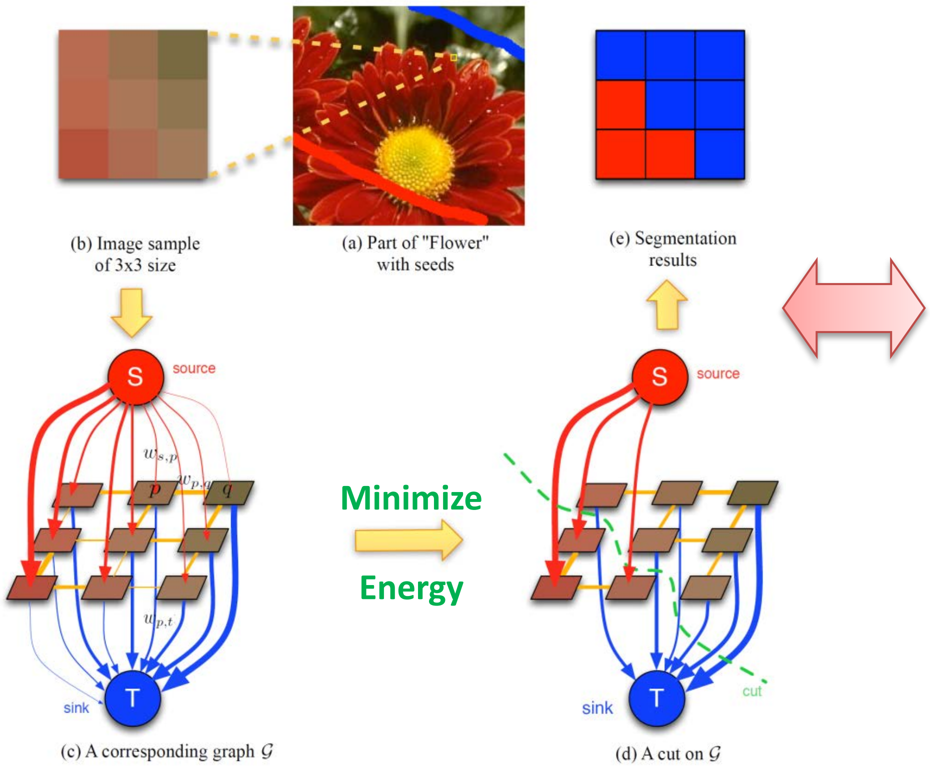
Graph cuts based segmentation



$$E(\mathcal{L}) = \sum_{p \in \mathcal{P}} D_p(l_p) + \lambda \cdot \sum_{\{p,q\} \in \mathcal{N}} V_{\{p,q\}}(l_p, l_q)$$

Data Term
(Prior Model)

Smoothness Term
(Likelihood Function)

State-of-the-art methods by graph cuts

- Boykov-Jolly's method:

$$D_p(l_p) = -\log \Pr(x_p|l_p) = -\log h(x_p; l_p)$$

Gray/Color Histogram Model

$$V_{\{p,q\}}(l_p, l_q) = \begin{cases} B_{p,q}, & \text{if } l_p \neq l_q \\ 0, & \text{if } l_p = l_q \end{cases}$$

$$B_{p,q} \propto \exp\left(-\frac{(x_p - x_q)^2}{2\sigma^2}\right) \cdot \frac{1}{dist(p,q)}$$

Penalty for Discontinuity

- Lazy Snapping:

$$D_p(l_p) = \frac{d_p^{l_p}}{d_p^1 + d_p^0}$$

$$d_p^{\mathcal{O}} = \min_i ||\boldsymbol{x}_p - \boldsymbol{m}_i^{\mathcal{O}}||$$
$$d_p^{\mathcal{B}} = \min_j ||\boldsymbol{x}_p - \boldsymbol{m}_j^{\mathcal{B}}||$$

Kmeans Clustering:
Distance from observed data to foreground/background cluster center

$$V_{\{p,q\}}(l_p, l_q) = \frac{|l_p - l_q|}{||\boldsymbol{x}_p - \boldsymbol{x}_q||^2 + 1}$$

- GrabCut:

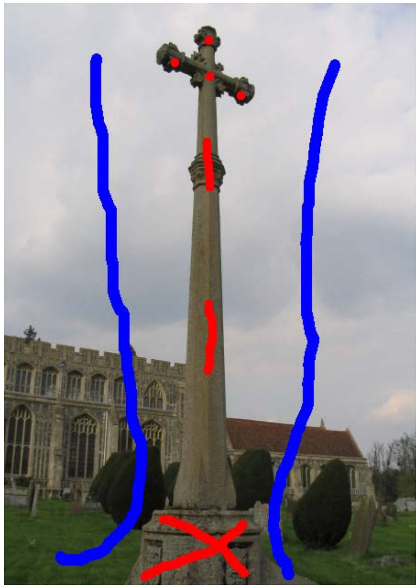
Gaussian Mixture Model (GMM)

$$D_p(l_p, k_p) = -\log \Pr(\boldsymbol{x}_p|l_p, k_p) = -\log \pi_p(l_p, k_p)\mathcal{N}(\boldsymbol{x}_p; \boldsymbol{\mu}(l_p, k_p), \boldsymbol{\Sigma}(l_p, k_p))$$

$$V_{\{p,q\}}(l_p, l_q) = \exp\left(-\frac{||\boldsymbol{x}_p - \boldsymbol{x}_q||^2}{2\langle(\boldsymbol{x}_p - \boldsymbol{x}_q)^2\rangle}\right) \cdot \frac{1}{dist(p,q)} \cdot \delta_{l_p \neq l_q}$$

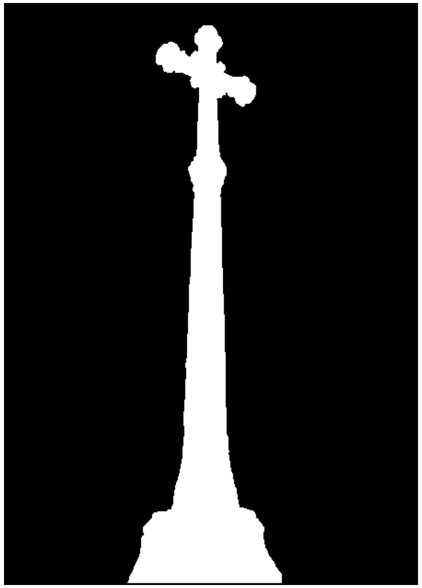
Drawbacks of graph-cut segmentation and our solutions

- Tuning of parameters λ and σ;
- Hard constraints ➡ Soft constraints;
- Definition of data term ➡ color, texture, shape features;



Initialization

Segmentation

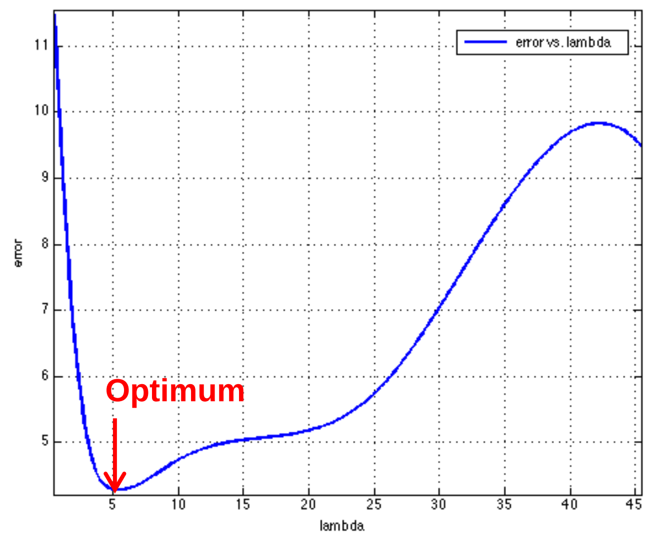


Ground Truth

- Selection of seeds ➡ Auto-Seeding for Melanoma.

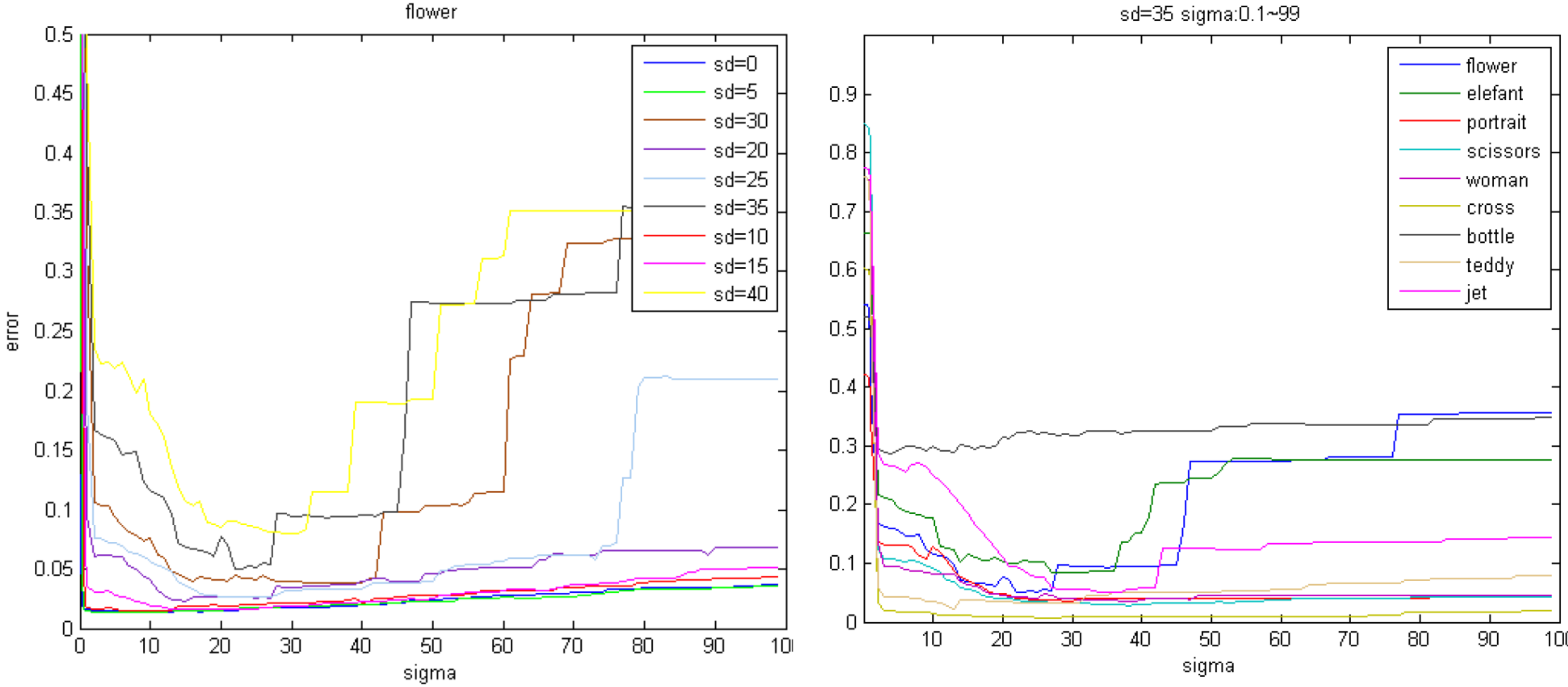
Graph cut: influence of parameter λ

- Parameter λ (Balancing Coefficient)



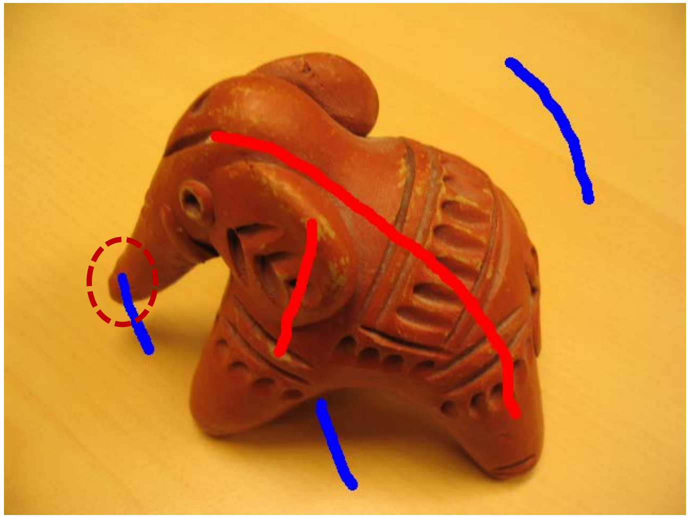
Graph cut: influence of parameter σ

- Parameter σ in smoothness term of Boykov-Jolly approach
  - ✓ Experiments on error-σ subject to different levels of Gaussian noise



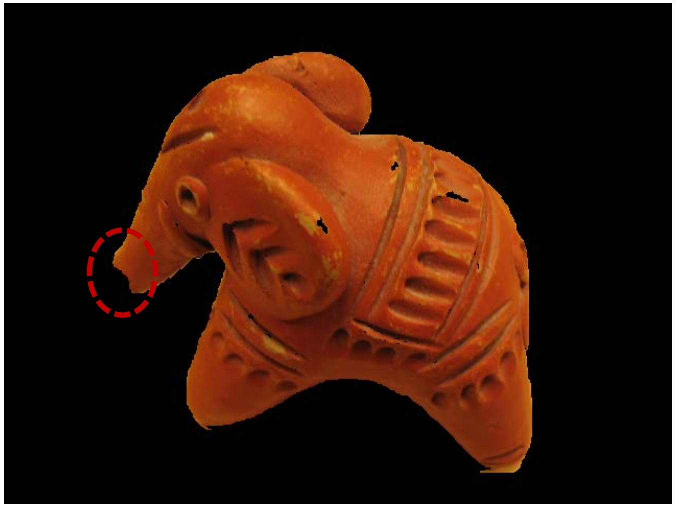
$$\sigma = \sqrt{\left\langle (I_p - I_q)^2 \right\rangle}$$

Graph cut: soft constraint vs. hard constraint?



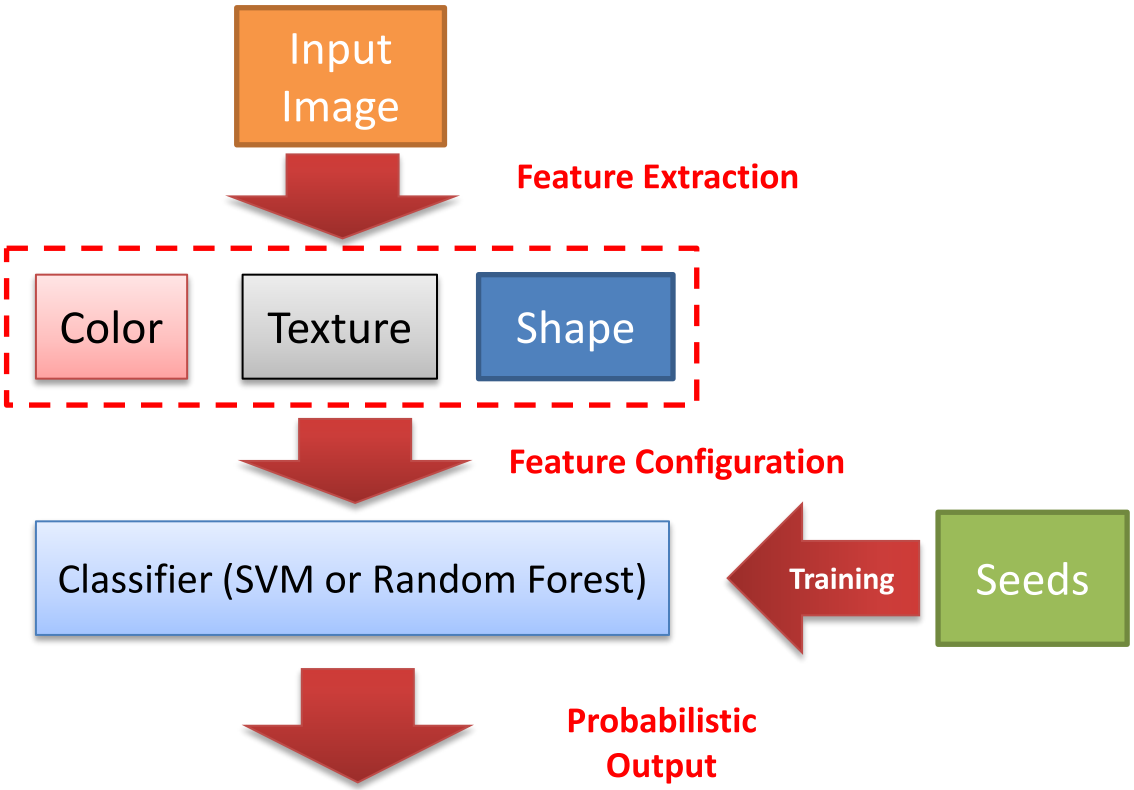
Soft

Hard



Data term

Schematic of our proposed multi-feature based graph-cut segmentation

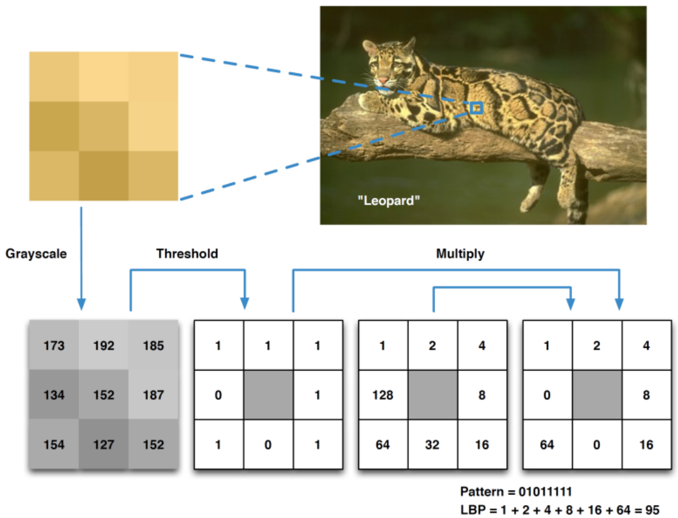


$$E(\mathcal{L}) = \boxed{\sum_{p \in \mathcal{P}} D_p(l_p)} + \lambda \cdot \sum_{\{p,q\} \in \mathcal{N}} V_{\{p,q\}}(l_p, l_q)$$

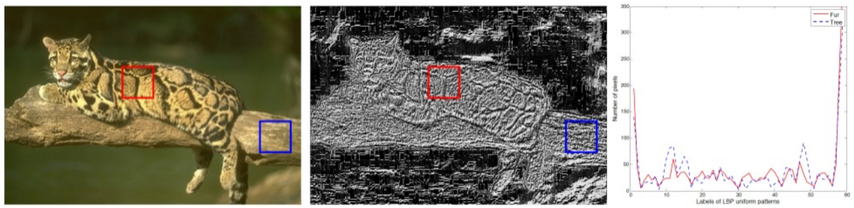
Data Term
(Prior Model)

Data term: texture feature

- ✓ Local Binary Pattern (LBP)

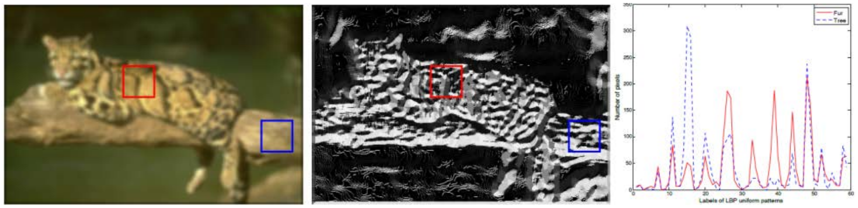


- ✓ Original LBP



Original Image | LBP Image | LBP Histogram

- ✓ With Gaussian Smoothing (GLBP)



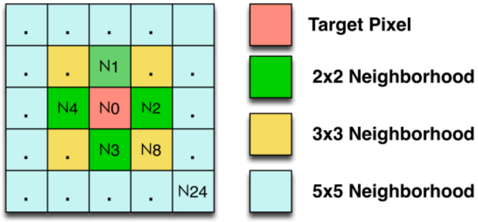
Original Image | LBP Image | LBP Histogram

Data term: shape feature

✓ Neighborhood Template

RGB Color &
Local Binary Pattern
(LBP) Texture

+



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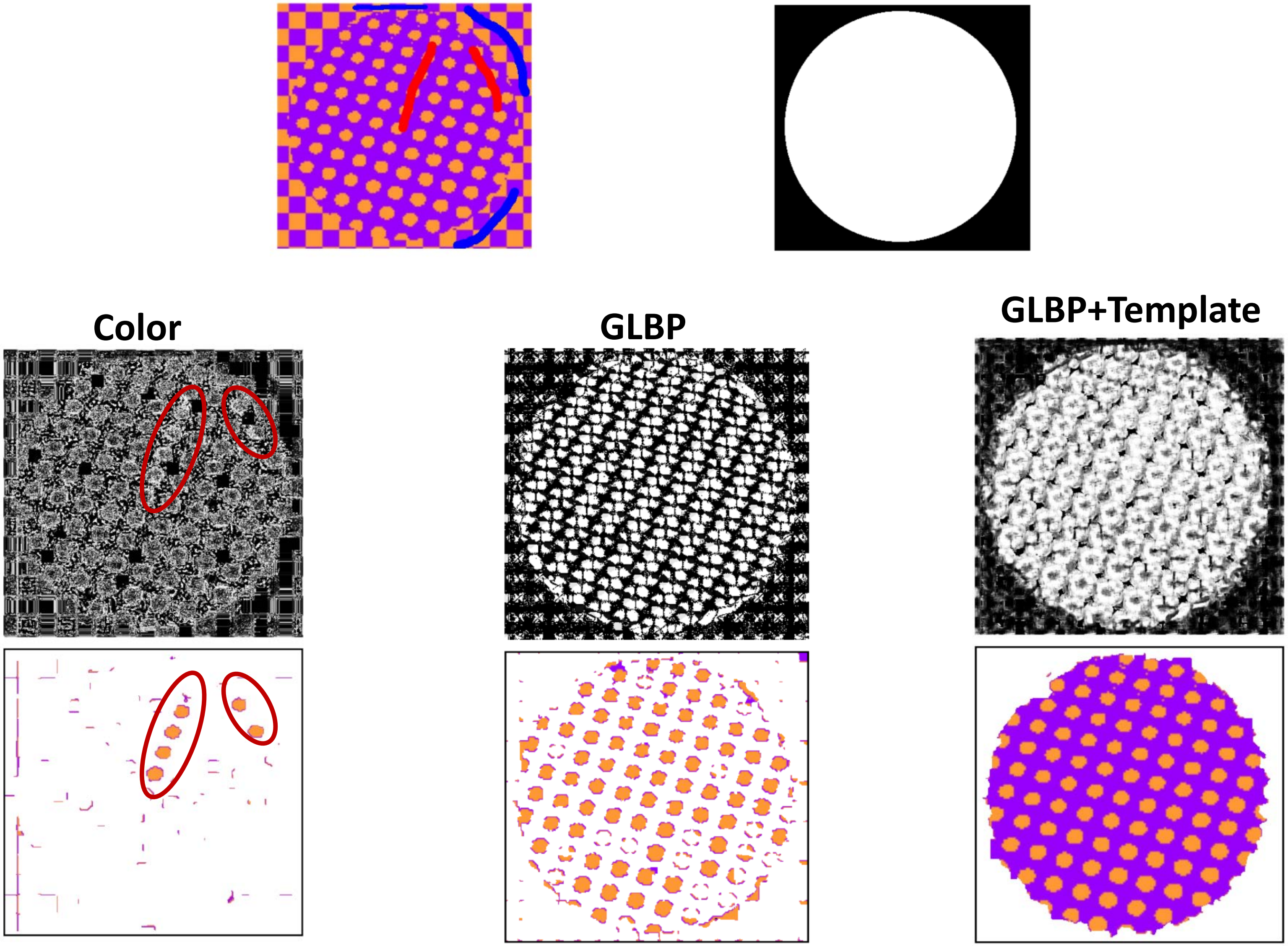
Multi-Feature Vector

$$\mathbf{F} = [R_0, G_0, B_0, T_0, \cdots, R_n, G_n, B_n, T_n]^\top$$

LBP texture feature

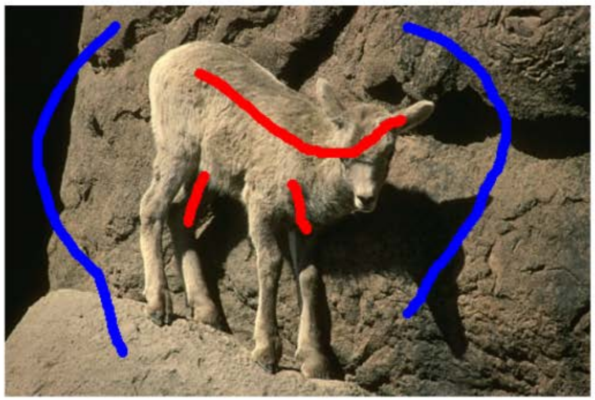
Qualitative evaluation on synthetic texture image



Qualitative evaluation on natural color images

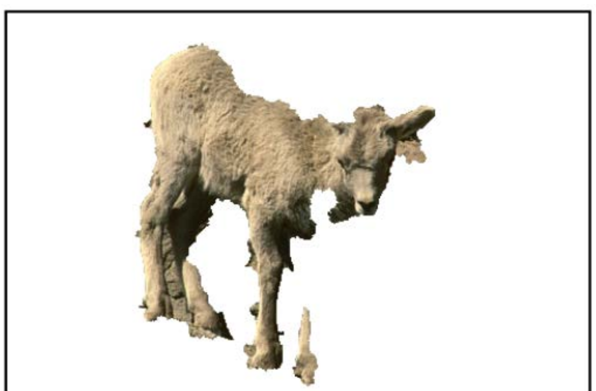
✓ Comparison of different combination of features on different images

Image with Seeds



Color

Color+Template



Color+GLBP+Template

Quantitative evaluation on natural color images

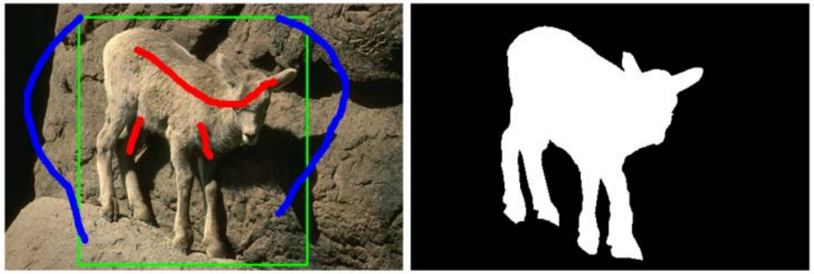
✓ Comparison of different combination of features measured by error rate

Input image	Feature / Classifier	Color	Color + LBP	Color + GLBP	Color+Temp	Color + LBP+Temp	Color + GLBP+Temp
Leopard	SVM	50.99	46.07	42.75	12.86	12.31	**11.84**
	RF	13.32	14.40	14.15	16.17	**13.40**	15.60
Swimmer	SVM	27.24	17.76	26.98	15.40	14.62	**13.10**
	RF	14.17	14.23	**13.99**	20.29	20.94	16.58
Cross	SVM	127.78	107.92	109.20	70.59	**6.53**	23.23
	RF	15.43	12.90	12.50	4.00	**3.99**	4.04
Grave	SVM	84.92	84.91	27.54	33.94	**8.40**	23.48
	RF	7.28	**7.11**	6.67	8.39	8.29	7.61
Plane	SVM	14.60	14.65	14.53	**5.44**	10.19	10.21
	RF	18.97	11.32	22.48	18.73	18.48	**6.78**
Japanese	SVM	17.53	10.08	12.25	**1.66**	2.85	2.82
	RF	2.89	2.87	2.13	1.94	1.63	**1.52**
Sheep	SVM	62.92	66.40	57.63	25.88	27.87	**20.66**
	RF	55.92	48.65	44.64	47.23	45.36	**29.56**
Boat	SVM	36.86	36.84	36.84	144.98	15.11	**9.64**
	RF	**10.65**	10.76	10.84	12.40	12.37	12.40

Blue color highlights the best performance by either ***SVM*** or ***RF***

Qualitative evaluation on natural color images

- ✓ Comparison of our approach against state-of-the-art methods



Quantitative evaluation on natural color images

✓ Comparison of our approach against state-of-the-art methods

Error ϵ (%) \ Method / Input image	Boykov-Jolly	Lazy Snapping	GrabCut	Our approach
Texture	27.46	11.65	19.46	**3.81**
Leopard	37.22	55.95	47.16	**11.84**
Grave	20.63	10.89	**5.15**	7.61
Cross	75.81	18.43	57.82	**3.99**
Swimmer	16.25	**8.02**	165.20	13.10
Plane	15.59	19.00	38.10	**6.78**
Japanese	6.33	5.29	3.58	**1.52**
Sheep	55.23	70.97	51.43	**20.66**
Birds	19.05	18.64	25.50	**10.82**
Boat	18.60	17.17	10.58	**9.64**

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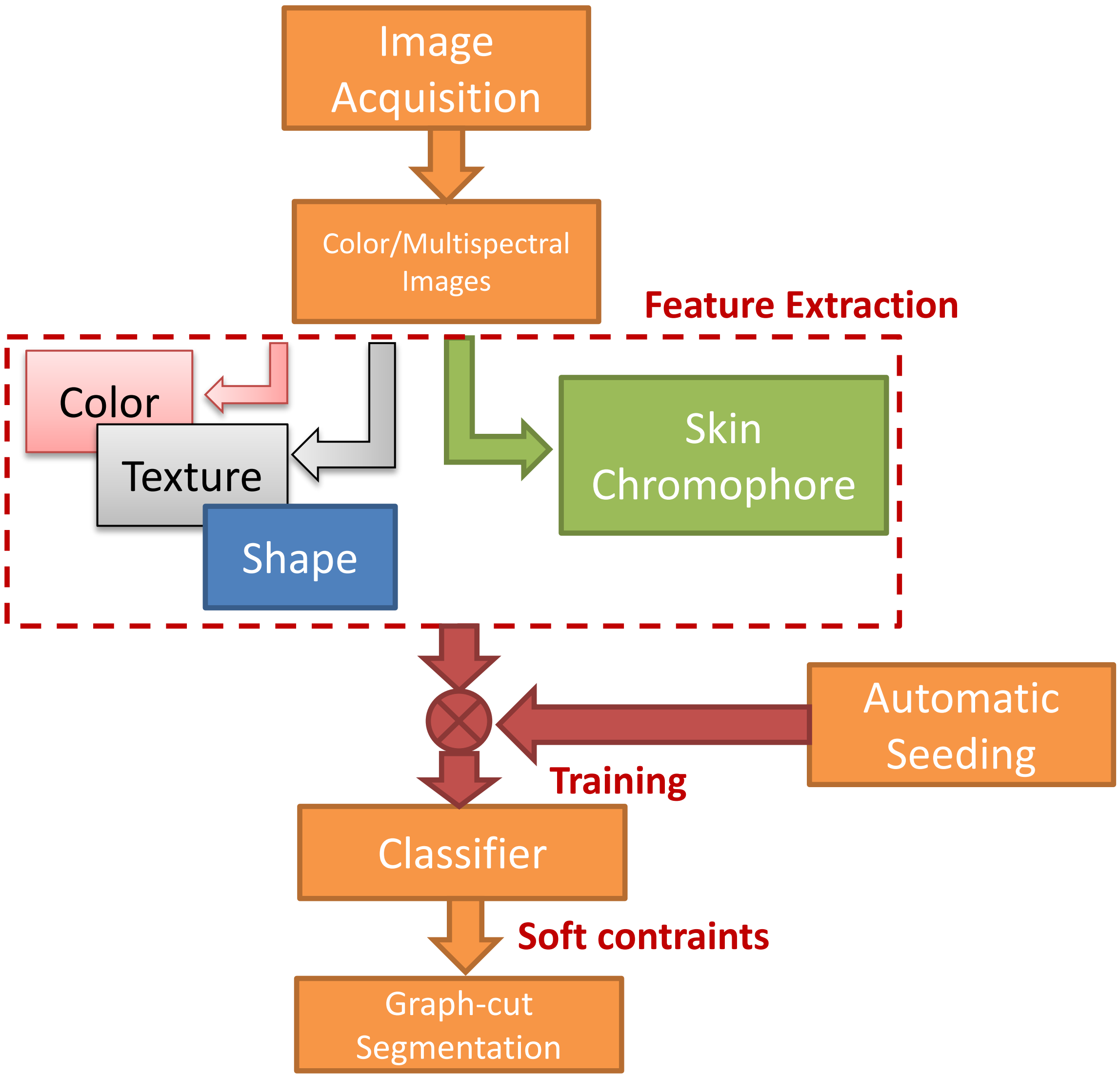
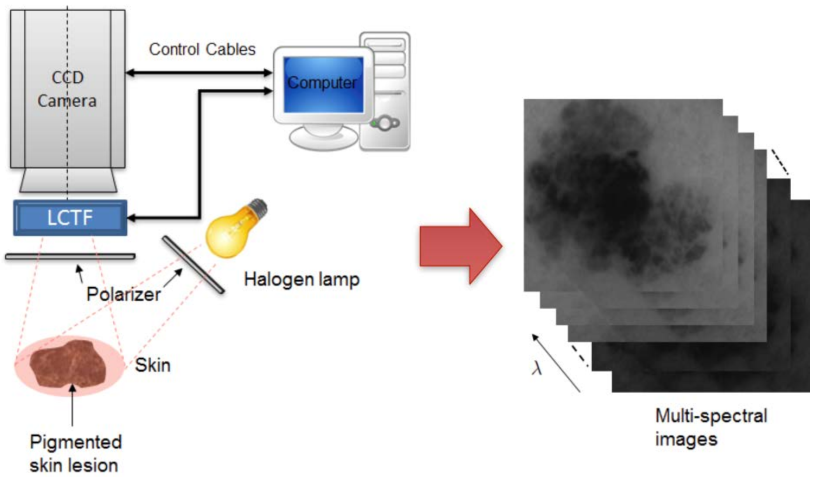
Schematic of segmentation of melanoma



Skin images

- Multispectral Image Acquisition:



Multi-spectral images of melanoma (469x436 pixels) at 26 wavelength sampled equally from 450 nm to 700 nm.

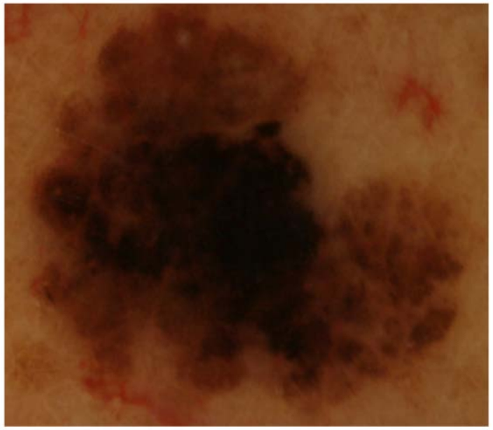
- Pre-Processing: Calibration

✓ Removal of Inhomogeneities of illumination

✓ Validate the reproducibility of spectral reflectance of skin.

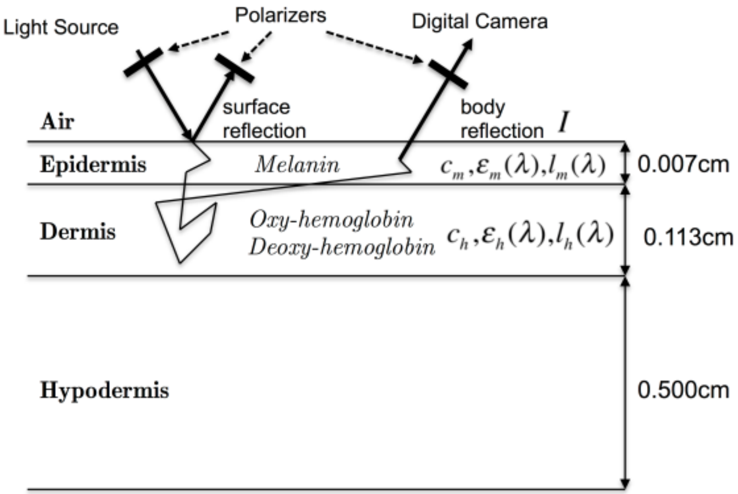
$$\boldsymbol{R}(\lambda) = \frac{\boldsymbol{S}(\lambda) - \boldsymbol{D}}{\boldsymbol{S}_{\mathrm{ref}}(\lambda) - \boldsymbol{D}}$$

- RGB color image



Skin Structure & Optical Property

Schematic of optical pathway in a 3-layered skin model



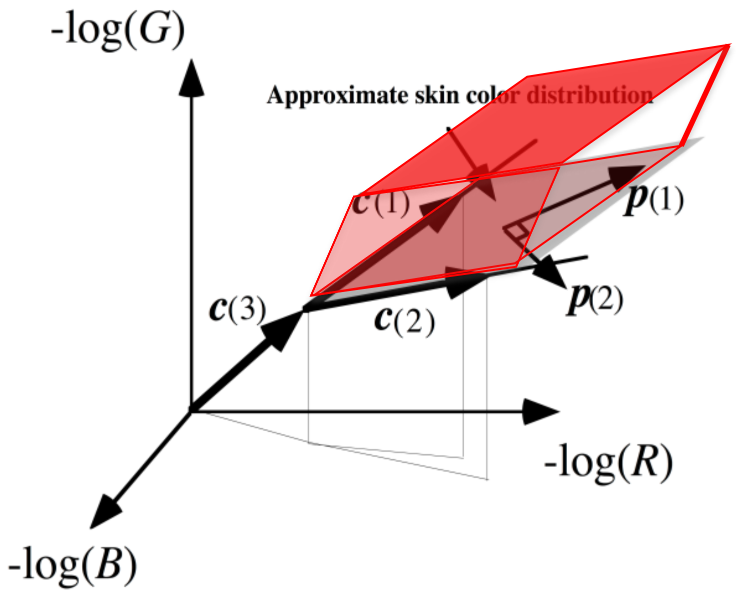
Based on *Beer-Lambert Law*, absorbance of skin model can be expressed for each pixel of skin image as:

$$A(\lambda) = \log(1/R(\lambda))$$

$$= \epsilon_{\mathrm{HbO2}}(\lambda) l_{\mathrm{HbO2}}(\lambda) c_{\mathrm{HbO2}} + \epsilon_{\mathrm{Hb}}(\lambda) l_{\mathrm{Hb}}(\lambda) c_{\mathrm{Hb}} + \epsilon_{\mathrm{Mel}}(\lambda) l_{\mathrm{Mel}}(\lambda) c_{\mathrm{Mel}}$$

Chromophore extraction: Image-processing based approaches

RGB color space based (Tsumura's method):



Optical density domain

↓

2D plane by PCA

↓

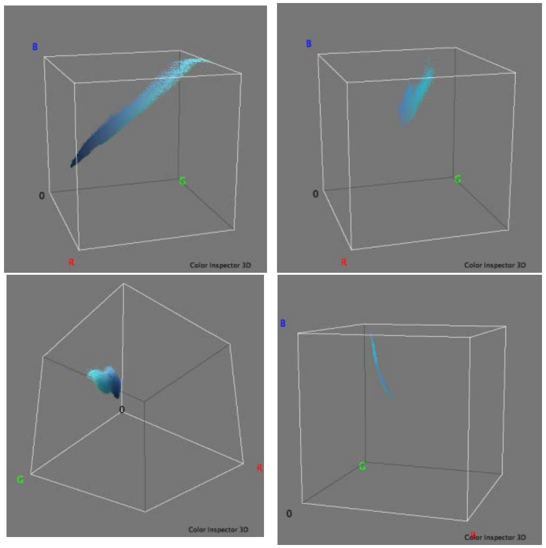
2 quantity vectors by ICA

↓

Estimation of hemoglobin and melanin

Modification Version:
SF^2 Method

Chromophore extraction: Image-processing based approaches

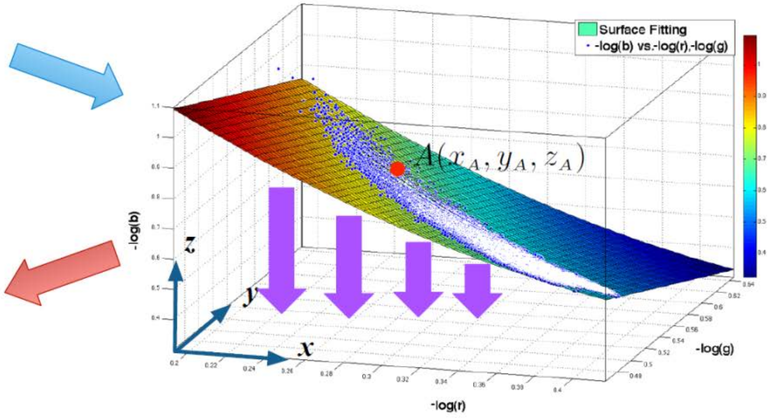


✓ Weakness of Tsumura's method

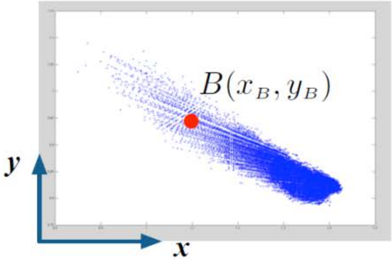
- Unrobust to variation of illumination;
- Lies in 3D surface where PCA inadequate;
- Valid only for small region of skin sample;

✓ Proposed **S**urface **F**itting and **F**lattening (**SF**^{2}) Method

(a) Input skin image with shadow



(b) Logarithmic Nrgb color space



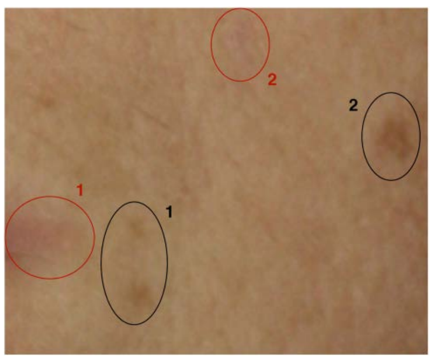
(c) Flattened 2-dimensional plane

Results: on small region of facial skin

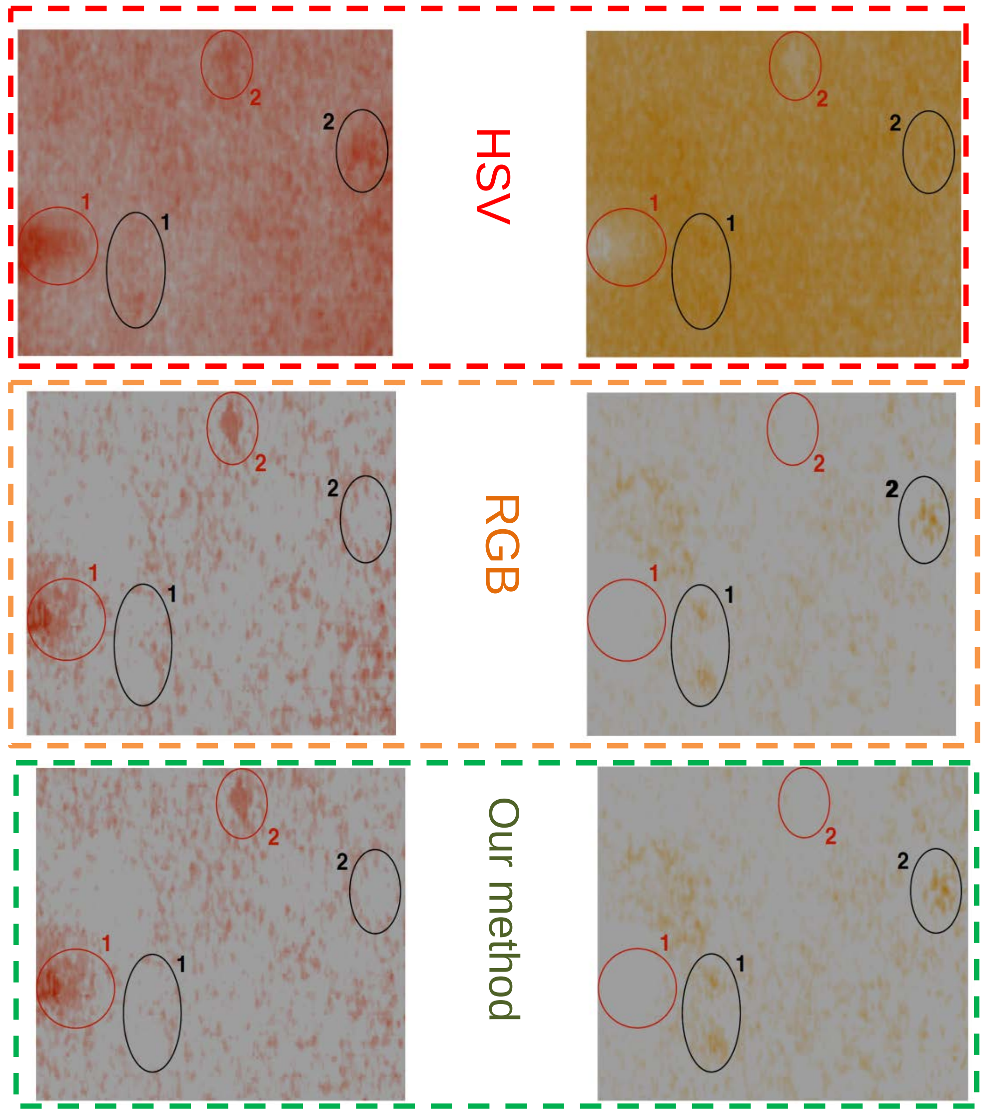
✓ **Skin chromophore extraction results of small-region facial skin**

Lip and Pimple

Freckles



Small region (313x257 pixels) of facial skin images



Chromophore extraction: Physical-model based approaches on RGB and Multispectral images

$$\begin{bmatrix} \log(1/\boldsymbol{R}(\lambda_1)) \\ \vdots \\ \log(1/\boldsymbol{R}(\lambda_m)) \end{bmatrix} = \begin{bmatrix} \epsilon_{\text{HbO2}}(\lambda_1) & \epsilon_{\text{Hb}}(\lambda_1) & \epsilon_{\text{Mel}}(\lambda_1) \\ \vdots & \vdots & \vdots \\ \epsilon_{\text{HbO2}}(\lambda_m) & \epsilon_{\text{Hb}}(\lambda_m) & \epsilon_{\text{Mel}}(\lambda_m) \end{bmatrix} \begin{bmatrix} \boldsymbol{c}_{\text{HbO2}} \\ \boldsymbol{c}_{\text{Hb}} \\ \boldsymbol{c}_{\text{Mel}} \end{bmatrix}$$

Matrix → $\boldsymbol{X} = \boldsymbol{A}\boldsymbol{S}$

- Mixing matrix ***A*** **is unknown**:
  - ✓ Blind Source Separation (BSS) based methods (e.g. **NMF**)
- Mixing matrix ***A*** **is given by tabulated extinction coefficient of three chromophores**:
  - ✓ Proposed Model-Fitting approach:

$$\boldsymbol{S} = \boldsymbol{A}_{\text{tabulate}}^{-1}\boldsymbol{X}$$

Color Image

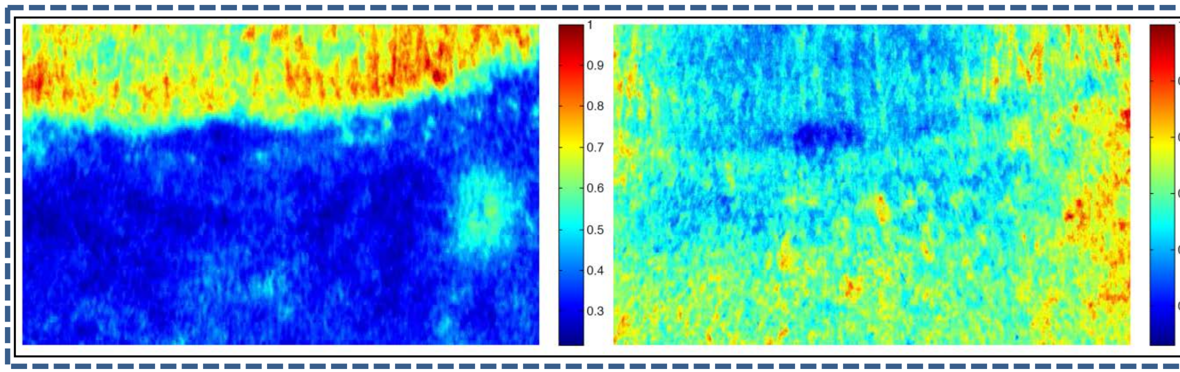
$$\underset{\boldsymbol{A}_{\text{tabulated}}}{\arg\min} \; \|\boldsymbol{X} - \boldsymbol{A}_{\text{tabulated}}\boldsymbol{S}\|^2$$
$$\textit{Subject to}: \boldsymbol{S} \geq 0$$

Multispectral Image

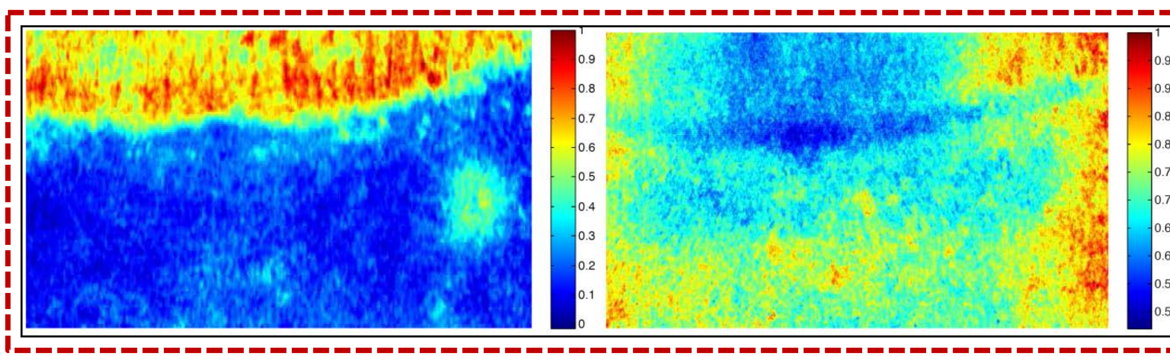
Qualitative evaluation on color facial images

- Based on the dermatologic knowledges：
  - higher hemoglobin and lower melanin for lip and pimple

Lip and Pimple



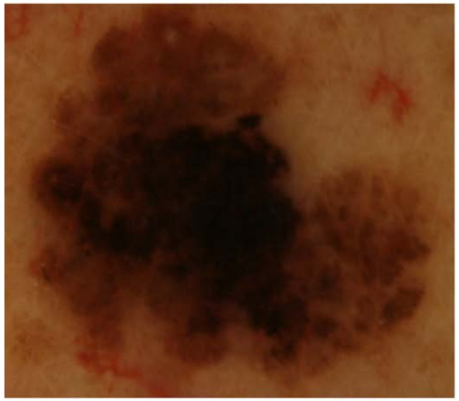
NMF



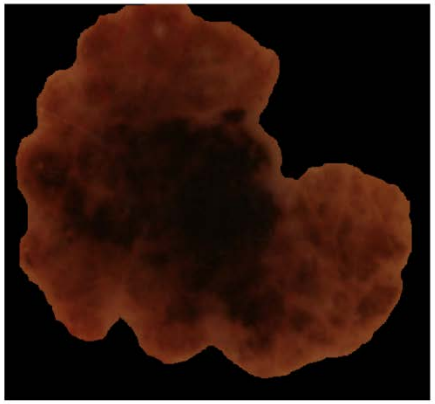
Model Fitting

Quantitative evaluation on color melanoma image

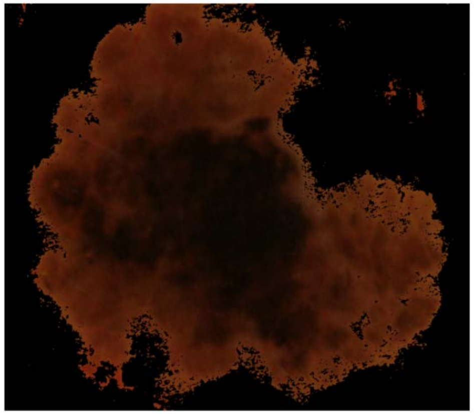
- ✓ Graph-cut based segmentation using RGB color+melanin+hemoglobin



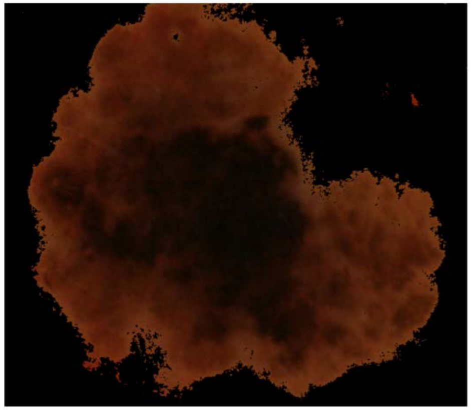
Melanoma



Manual Segmentation



NMF



Model-Fitting

Criterion \ Method	Model-Fitting	NMF
DSC	**0.982**	0.967
FNR	0.013	0.044
FPR	**0.023**	0.024

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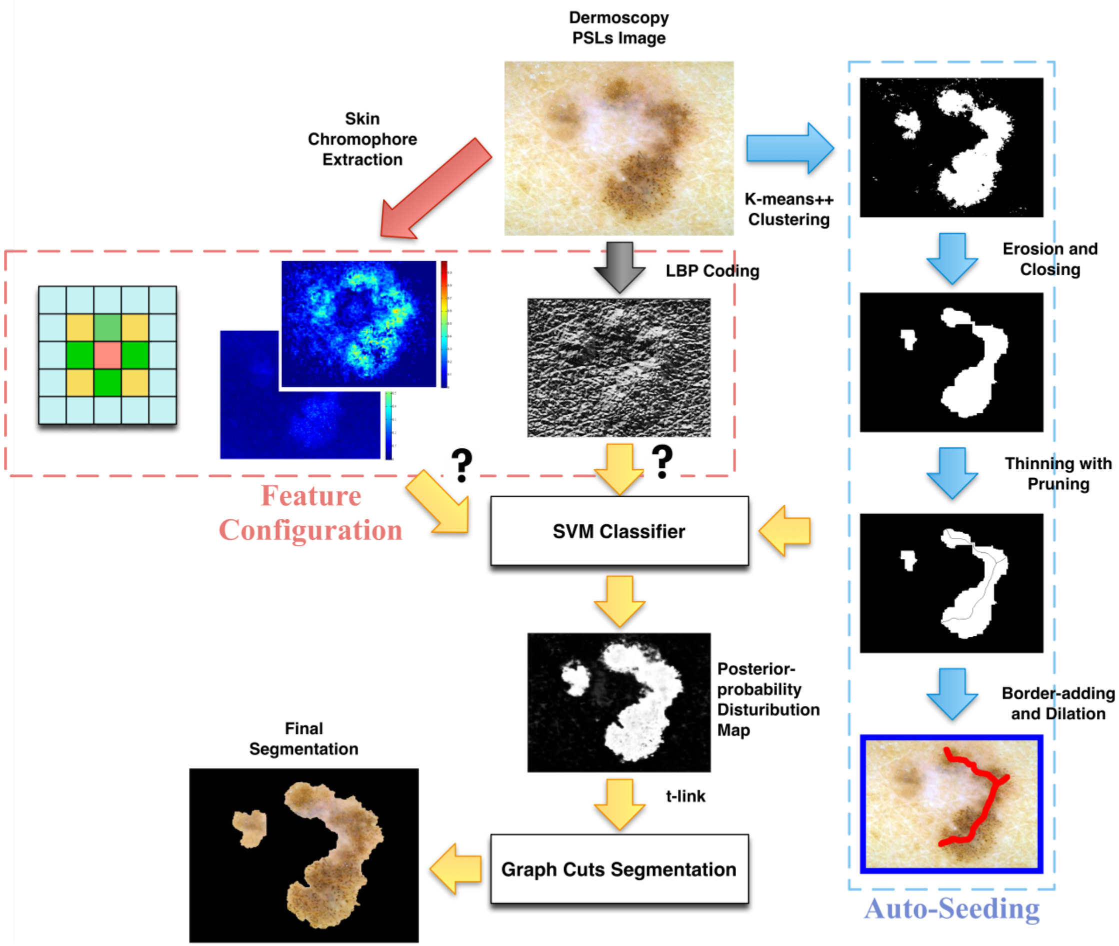
Automatic PSLs segmentation on dermoscopic images

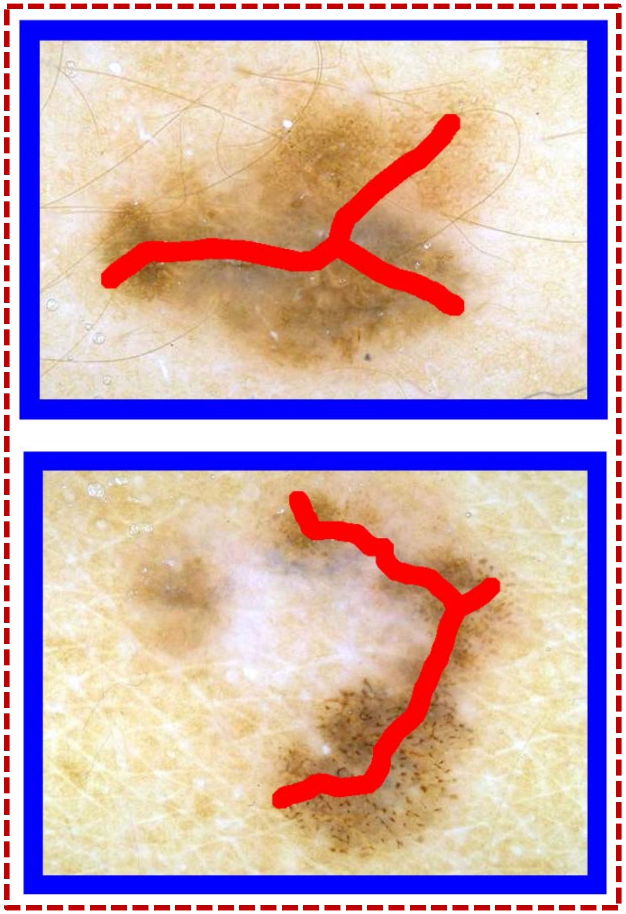
✓ **A**utomatic **P**SLs **S**egmentation (**APS**) Framework



Auto-Seeding Results

✓ Examples of Auto-Seeding results:

ambiguous border



Artifacts

Results of the Automatic PSLs segmentation on dermoscopic images

✓ Experiments on dermoscopic PSLs images

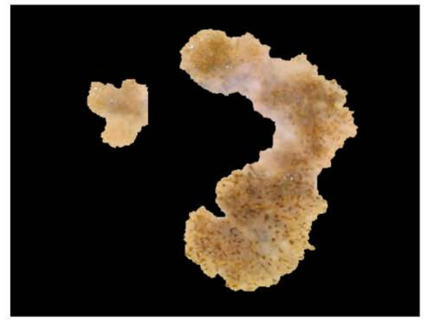
- 100 dermoscopic PSLs images (768X512) from a dermoscopy atlas
- 30 for training the parameter λ, 70 for testing
- 3 metrics for quantitative evaluation;

Automatic PSLs segmentation on dermoscopic images

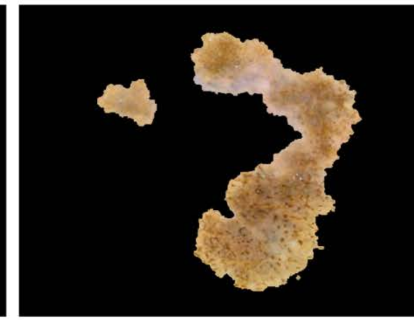
✓ Comparison of the proposed approach against classic graph-cut based methods:

Melanoma

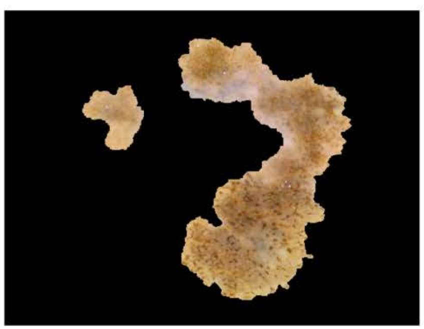
Manual Segmentation



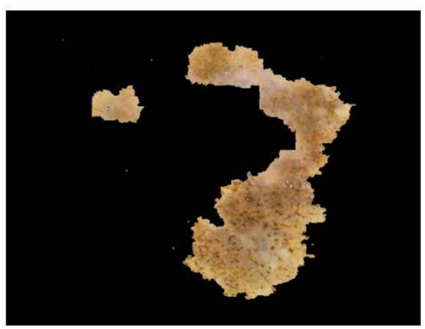
Color+Chromophore



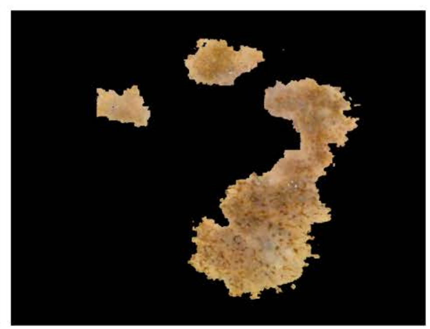
Color



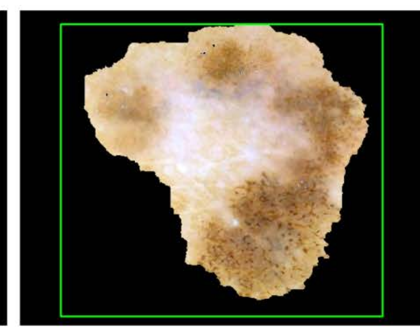
Color+GLBP



Lazy Snapping



Boykov-Jolly



GrabCut

Automatic PSLs segmentation on dermoscopic images

- ✓ **Quantitative evaluation of our proposed APS framework with different combination of features against other classic graph-cut based segmentation**

Criterion / Approach	DSC		Error ϵ		Precision		Recall	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Color	91.19	4.24	16.05	6.59	98.98	1.99	84.91	7.59
Color+LBP	91.41	3.89	15.70	6.47	98.74	2.02	85.69	7.68
Color+Chromo	**93.85**	**3.08**	**12.26**	**5.95**	98.36	1.68	88.27	7.56
LS	88.73	4.68	20.15	7.61	98.76	1.53	80.89	7.67
BKJ	88.70	5.00	20.13	7.90	**99.07**	**0.81**	80.66	8.14
GrabCut	87.90	9.90	29.97	32.39	84.37	16.45	**95.53**	**4.08**

Overview

- **Motivation:**

  Detection of **Melanoma** with computer-aided diagnosis system;

- **Methodology:**

  Graph-cut based image segmentation framework with **"soft" classification** and **visual features**;

- **Applications:**

  Segmentation of **Melanoma** and Automatic PSLs Segmentation (**APS**) framework;

  - **Skin chromophore extraction**
  - **Auto-Seeding**

- **Conclusion and Perspectives.**

Conclusion

✓ Contributions:

- Combining Classification Techniques and Graph-Cut Based Segmentation Framework
  - Definition of likelihood energy term (data term) by posterior classification of a classifier
  - Soft constraints
  - Construction of powerful feature vector

- Application to Skin Chromophore Extraction
  - Image based approach: Surface Fitting and Flattening (SF^2) approach
  - Physical property based approach: Model-Fitting Approach

- Application to Melanoma Detection
  - Robust and accurate segmentation tool: Automatic PSLs Segmentation (APS) Framework
  - Automatic selection of seed region (Auto-Seeding)
  - Chromophore feature in feature configuration