

Skin Hemoglobin and Melanin Quantification on Multi-spectral Images

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Outline

- Motivation/Objective
- Project *Melascan*
- Multi-spectral image acquisition
- Optics of human skin
- Different quantification methods
- Experimental results and evaluation
- Conclusion and perspective

Motivation/Objective

An accurate quantification of skin pigmentation is of primary importance for the objective diagnosis and grading of skin diseases.

Project *Melascan*

- **ANR** (French National Research Agency) funded project
- Innovative solution to detect and characterize progress over time of a skin cancer, using a standardized methodology and equipment, for the use of specialized and general physicians.

Project *Melascan*

What is *Melanoma*?

➤ **Melanoma** is the most dangerous form of skin cancer.

What does *Melanoma* look like?

➤ **A**symmetry, irregular **B**orders, multiple **C**olors,
Diameter >1/4inch, **E**volving



Fig.1. Melanoma

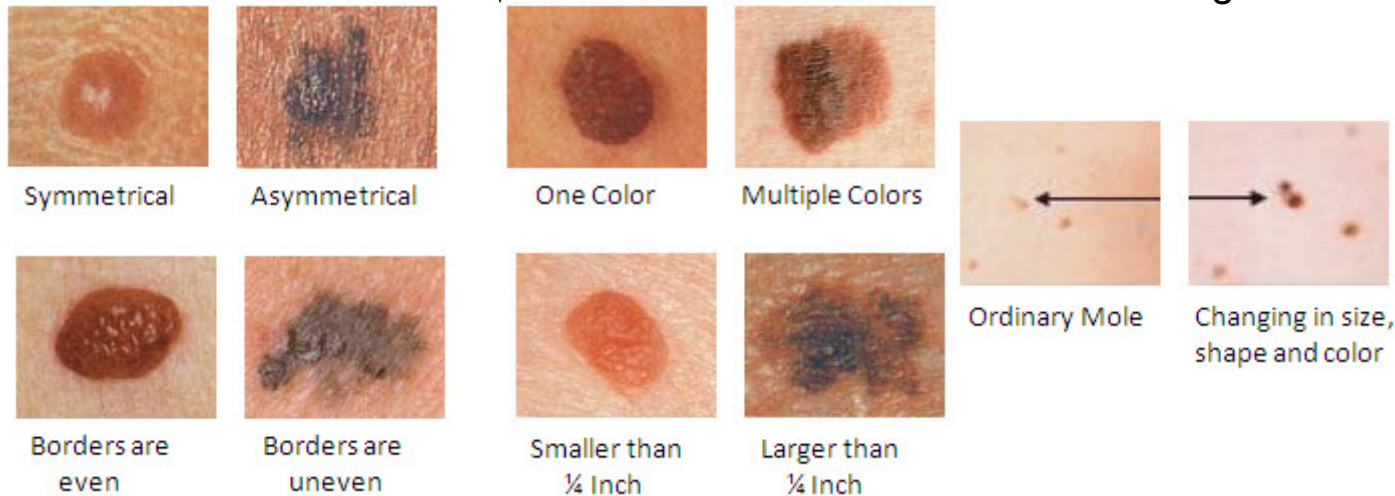


Fig. 2. 'ABCDE' of Melanoma

Multi-spectral Image Acquisition

Why Multi-spectral Images?

The integration of a multi-spectral light will allow:

- ✓ Reveal to the physicians the properties of non-visible skin characteristics (e.g. hemoglobin, melanin, collagen, etc.)
- ✓ Observation of the cutaneous in-depth layers.

Multi-spectral Image Acquisition

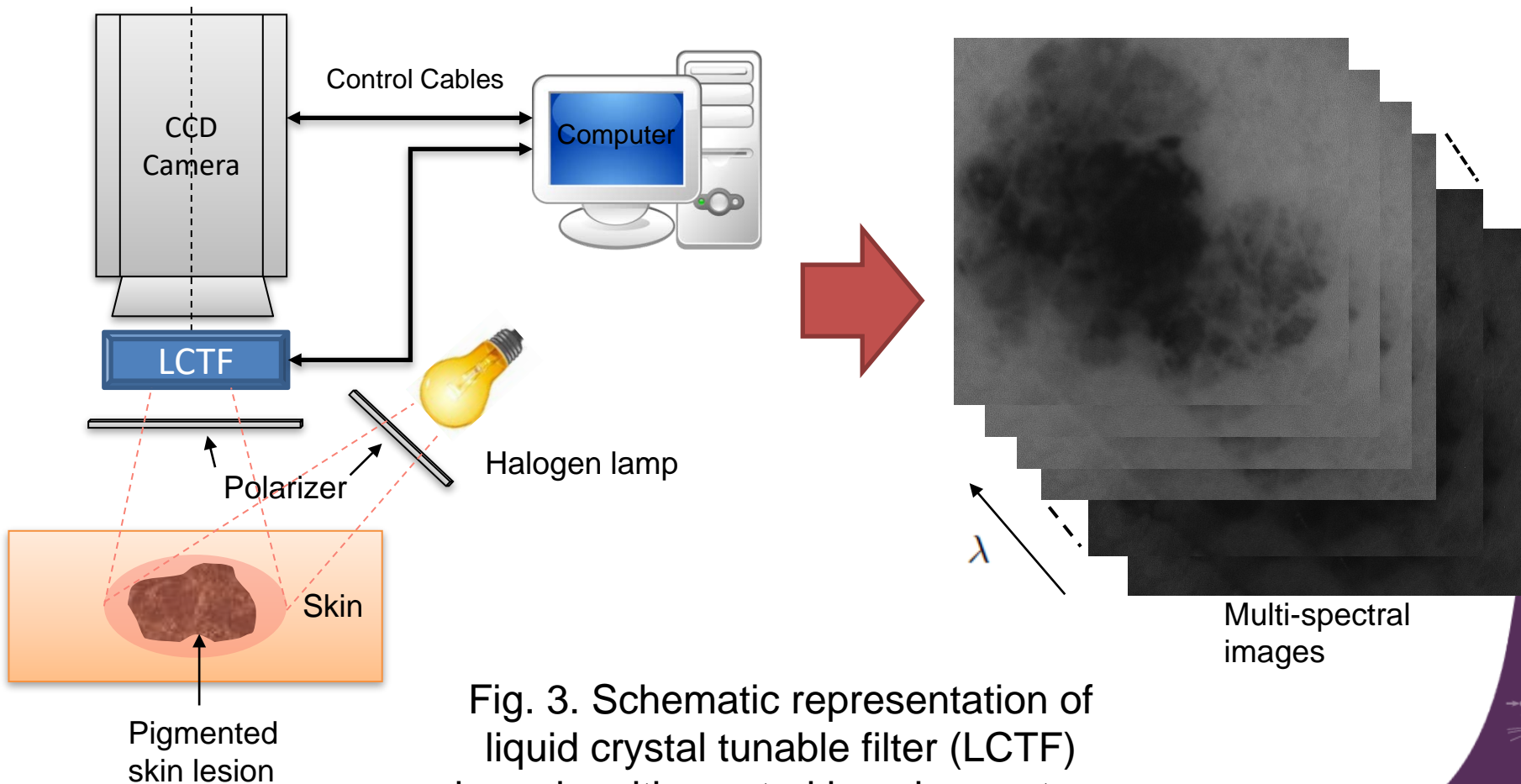


Fig. 3. Schematic representation of liquid crystal tunable filter (LCTF) based multi-spectral imaging system

Optics of Human Skin

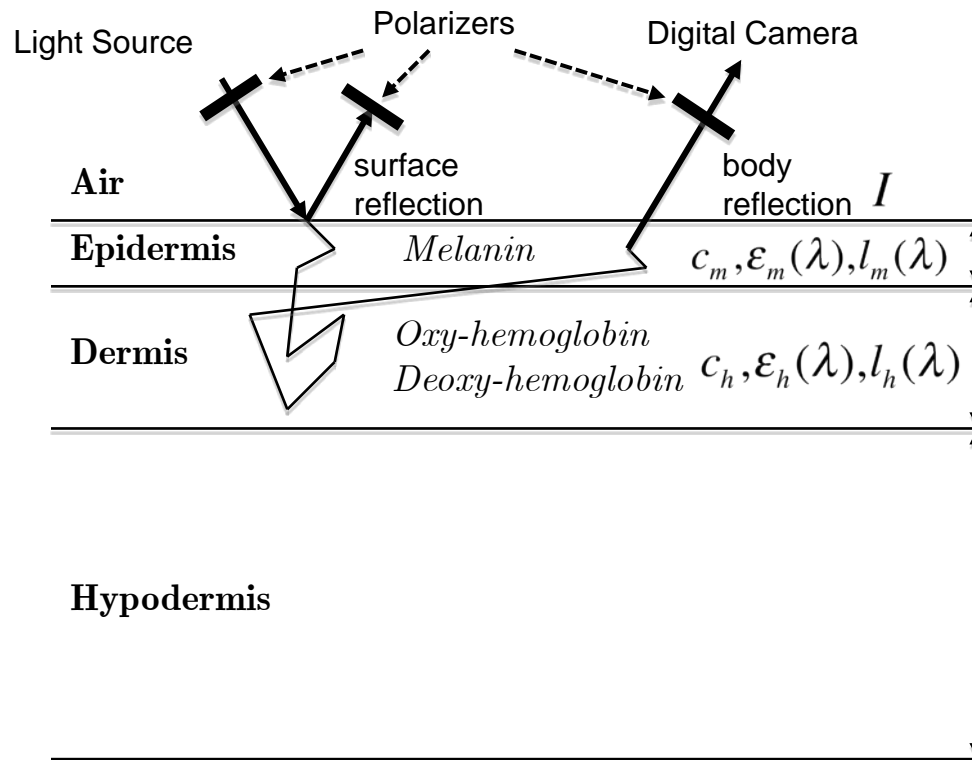


Fig.4. Schematic model of imaging process of three-layered model of skin

Optics of Human Skin

Based on *Beer-Lambert* law, absorbance $A(\lambda)$ of the 3-layer skin model at wavelength λ can be expressed as:

$$A(\lambda) = \log(1/R(\lambda)) \\ = \epsilon_{\text{Hb}}(\lambda) l_{\text{Hb}}(\lambda) c_{\text{Hb}} + \epsilon_{\text{Mel}}(\lambda) l_{\text{Mel}}(\lambda) c_{\text{Mel}}$$

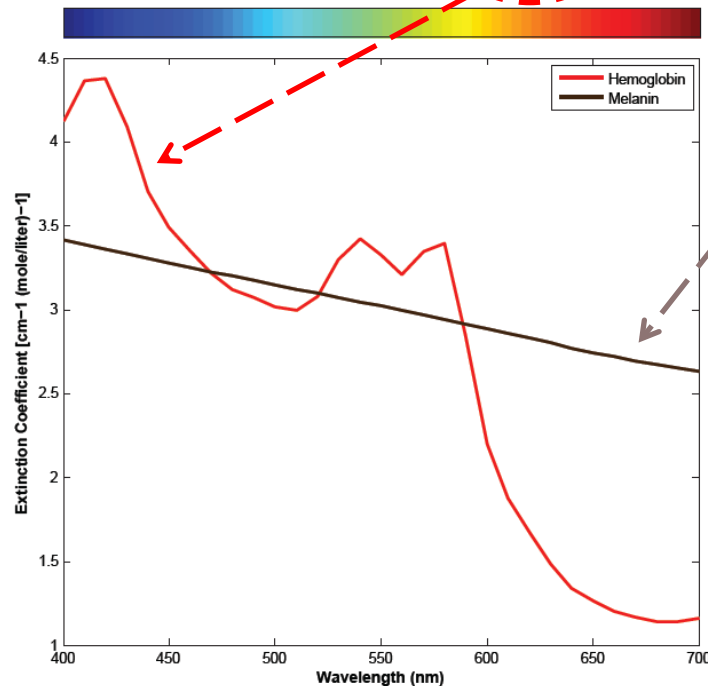


Fig. 5. Molar absorptivity spectra of chromophores

Erythema/Melanin Index

Takiwaki et al. proposed a method to derive erythema index (EI) image and melanin index (MI) image from multi-spectral images.

$$\begin{aligned}EI &= \log_{10}(1/R_{\lambda_1}) - \log_{10}(1/R_{\lambda_2}) \\MI &= \log_{10}(1/R_{\lambda_2})\end{aligned}$$

Non-negative Matrix Factorization Based Approach

Lee and Seung proposed a method of decomposition of multivariate data which explicitly enforces the non-negativity constraint on the values of the source data as well as the mixed data.

Non-negative Matrix Factorization Based Approach

The problem of source separation can be formulated as:

$$X = AS$$

In our particular case, the above equation can be specified as:

$$\begin{bmatrix} \log(1/\mathbf{r}(\lambda_1)) \\ \vdots \\ \log(1/\mathbf{r}(\lambda_m)) \end{bmatrix}_{m \times n} = \begin{bmatrix} \epsilon_h(\lambda_1) & \epsilon_m(\lambda_1) \\ \vdots & \vdots \\ \epsilon_h(\lambda_m) & \epsilon_m(\lambda_m) \end{bmatrix}_{m \times 2} \begin{bmatrix} \mathbf{c}_h \\ \mathbf{c}_m \end{bmatrix}_{2 \times n}$$

Non-negative Matrix Factorization Based Approach

Now the problem can be formulated as a maximum-likelihood problem with least-squares solution:

$$\begin{aligned} \mathbf{A}_{ML}, \mathbf{S}_{ML} &= \arg \max_{\mathbf{A}, \mathbf{S}} p(\mathbf{X} | \mathbf{A}, \mathbf{S}) \\ \Rightarrow F &= \arg \min_{\mathbf{A}, \mathbf{S}} \|\mathbf{X} - \mathbf{A}\mathbf{S}\|^2 \\ \text{Subject to : } &\mathbf{A} \geq 0, \mathbf{S} \geq 0 \end{aligned}$$

Initialization

$$\mathbf{S}_{\text{initial}} = \begin{bmatrix} \mathbf{E}\mathbf{I} \\ \mathbf{M}\mathbf{I} \end{bmatrix}$$

$$\arg \min_{\mathbf{A}_{\text{initial}}} \|\mathbf{X} - \mathbf{A}_{\text{initial}} \mathbf{S}_{\text{initial}}\|^2$$

$$\text{Subject to : } \mathbf{A}_{\text{initial}} \geq 0$$

Model-Fitting Based Approach

A more accurate model introduced including oxy-hemoglobin and deoxy-hemoglobin based on the oxygen-saturation of hemoglobin.

$$X = AS$$



$$\begin{bmatrix} \log(1/\mathbf{r}(\lambda_1)) \\ \vdots \\ \log(1/\mathbf{r}(\lambda_m)) \end{bmatrix} = \begin{bmatrix} \epsilon_{\text{hO}_2}(\lambda_1) & \epsilon_{\text{h}}(\lambda_1) & \epsilon_{\text{m}}(\lambda_1) \\ \vdots & \vdots & \vdots \\ \epsilon_{\text{hO}_2}(\lambda_m) & \epsilon_{\text{h}}(\lambda_m) & \epsilon_{\text{m}}(\lambda_m) \end{bmatrix} \begin{bmatrix} C_{\text{hO}_2} \\ C_{\text{h}} \\ C_{\text{m}} \end{bmatrix}$$

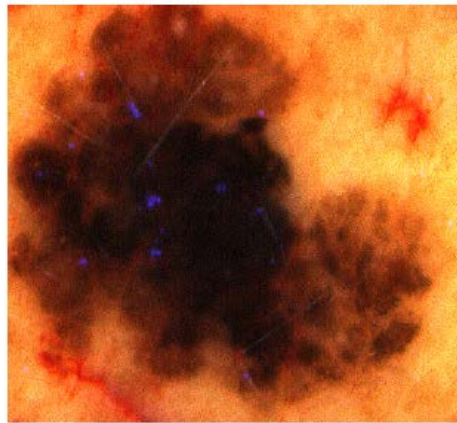
Model-Fitting Based Approach

Solutions of this over-determined system can be obtained using least-squares estimation with a single constraint:

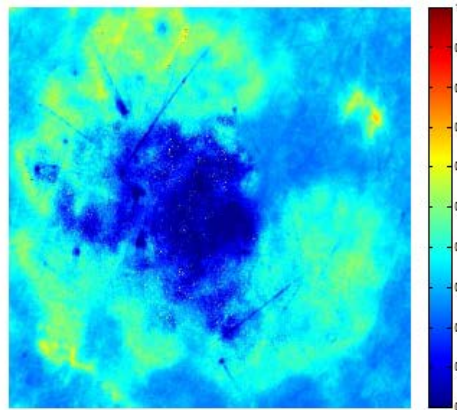
$$\arg \min_{\mathbf{A}_{\text{tabulated}}} \|\mathbf{X} - \mathbf{A}_{\text{tabulated}} \mathbf{S}\|^2$$

Subject to : $\mathbf{S} \geq 0$

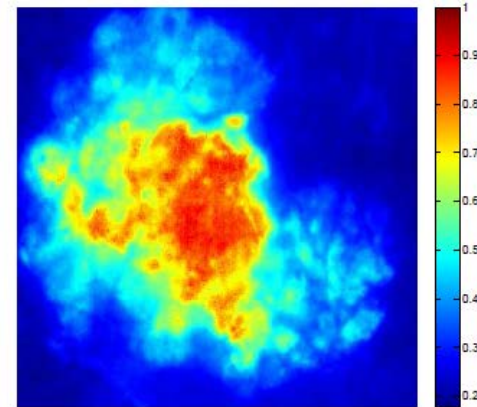
Results & Qualitative Evaluation



(a) Reconstructed Color Image

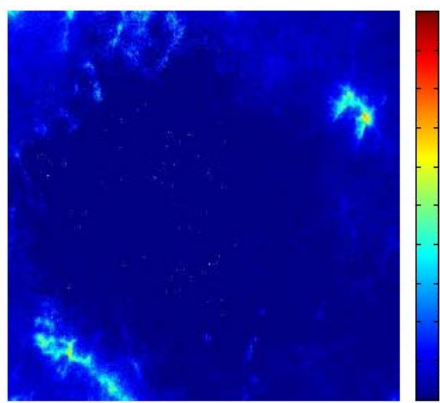


(b) Hemoglobin by NMF

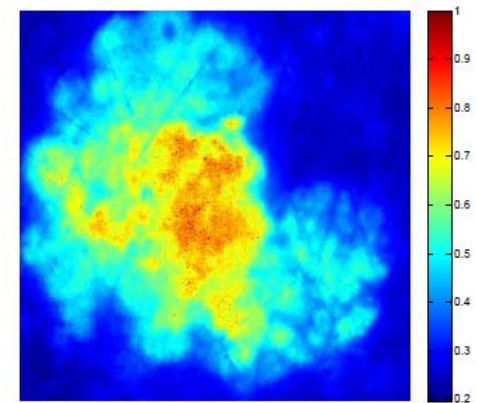


(c) Melanin by NMF

Fig.6. Comparison of hemoglobin and melanin concentration cartographies.



(d) Hemoglobin by MF



(e) Melanin by MF

Results & Quantitative Evaluation

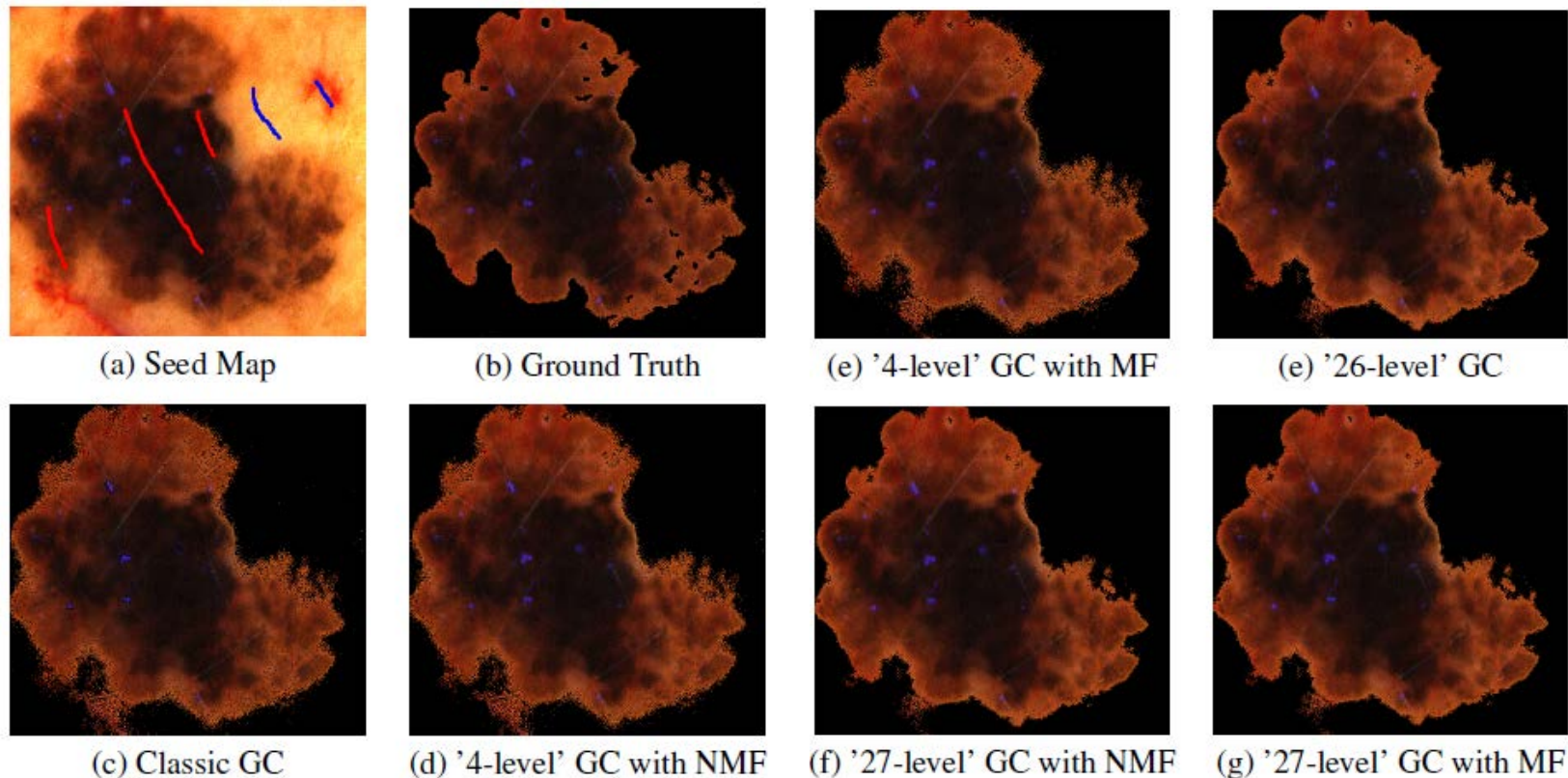


Fig.7. Comparison of graph-cut segmentation results

Results & Quantitative Evaluation

Table 1. Comparison of Segmentation Accuracy (Part 1)

	4-level MF	4-level NMF	Classic GC
DSC	0.954	0.950	0.943
FNR	0.009	0.011	0.026
FPR	0.085	0.092	0.091

Table 2. Comparison of Segmentation Accuracy (Part 2)

	27-level MF	27-level NMF	26-level GC
DSC	0.965	0.963	0.962
FNR	0.008	0.008	0.008
FPR	0.065	0.067	0.068

Conclusion & Perspective

By means of two comparative experiments based on:

➤ Dermatologic knowledge

➤ Graph-cut (GC) segmentation

Model-fitting approach (MF) outperforms Non-negative Matrix Factorization (NMF) based approach.

In future work, **scattering** and **penetration depth** will be taken into account in skin optics model.

THANK YOU!

Any QUESTIONS?

