Reproduction of Multispectral Images using Autotypical Color Mixture

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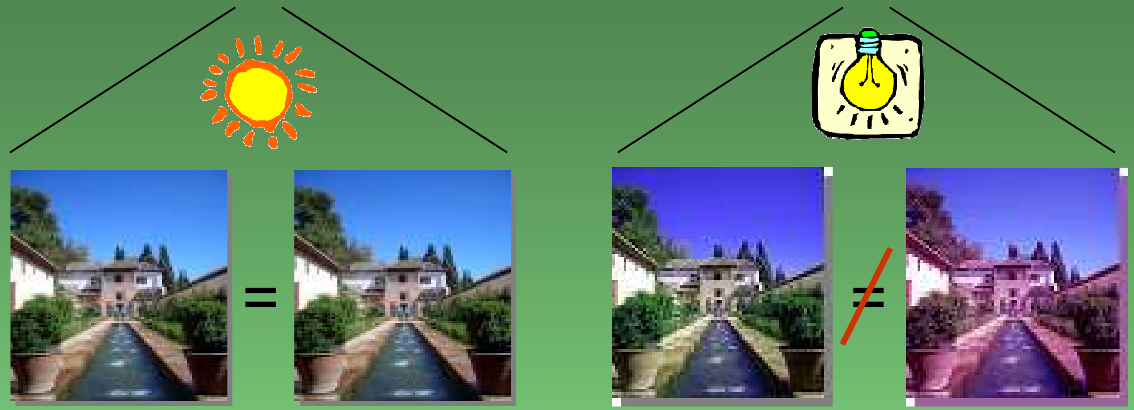
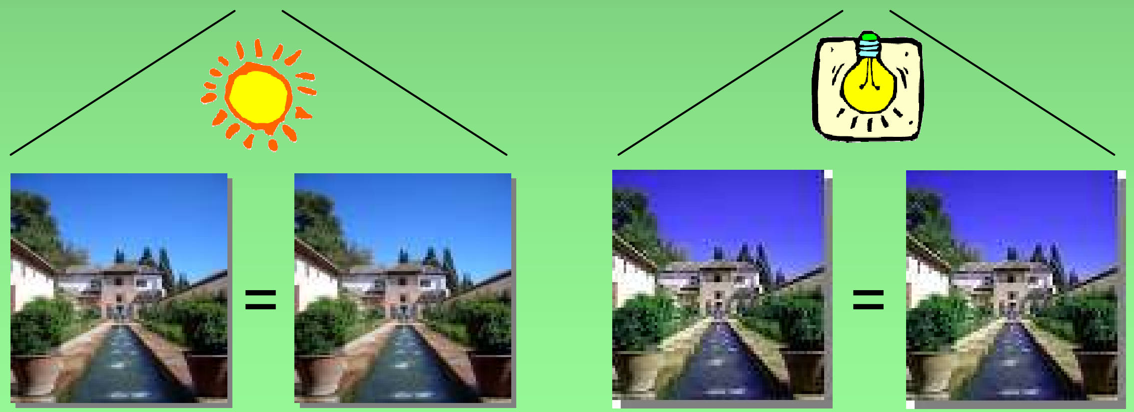
Motivation and Problems

Motivation and Problems

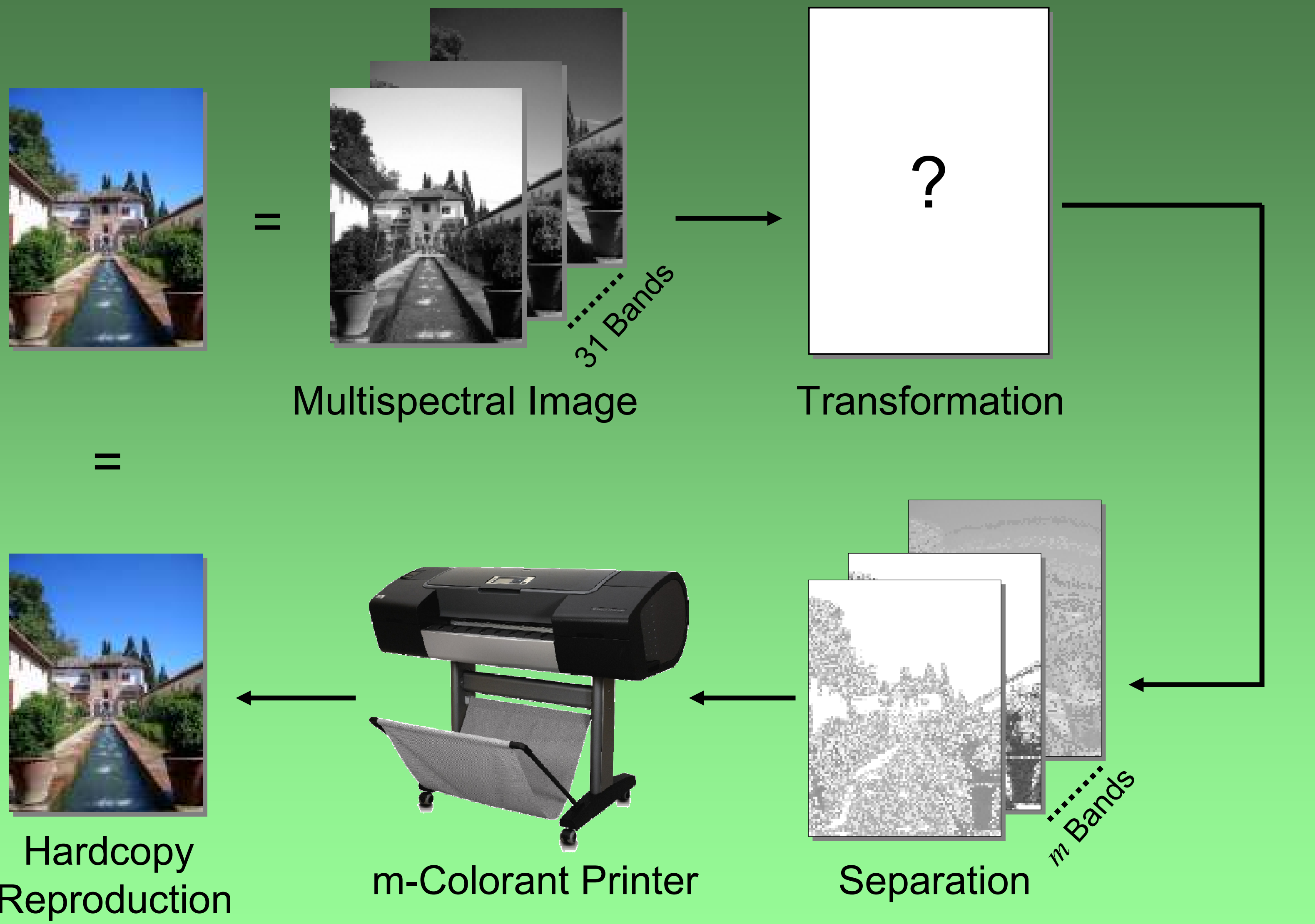
Traditional Reproduction: Systematic observer + illuminant metamerism



Multispectral Reproduction:



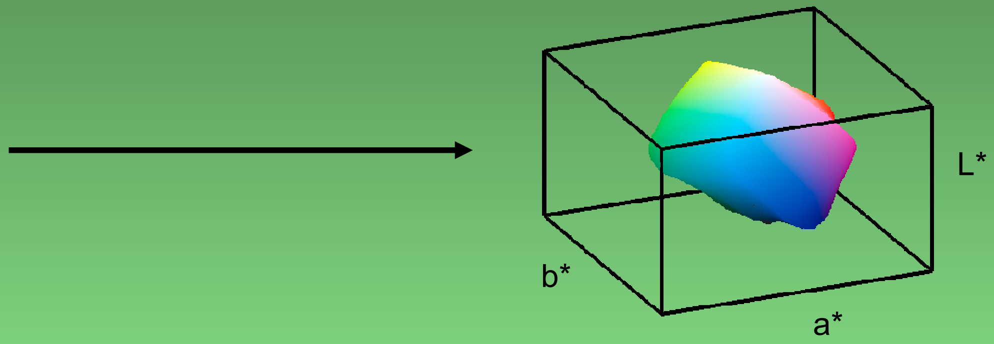
Motivation and Problems



Motivation and Problems

Problems:

- Spectral printer gamut is limited $\Rightarrow$ spectral gamut mapping is necessary



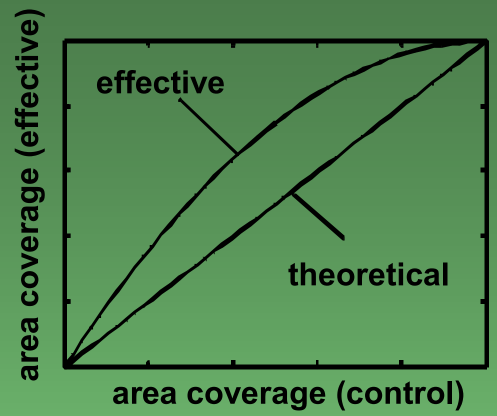
- Spectral printer gamut is several dimensions smaller than the dimension of all natural reflectances

$\Rightarrow$ nearly each given spectrum has to be gamut mapped

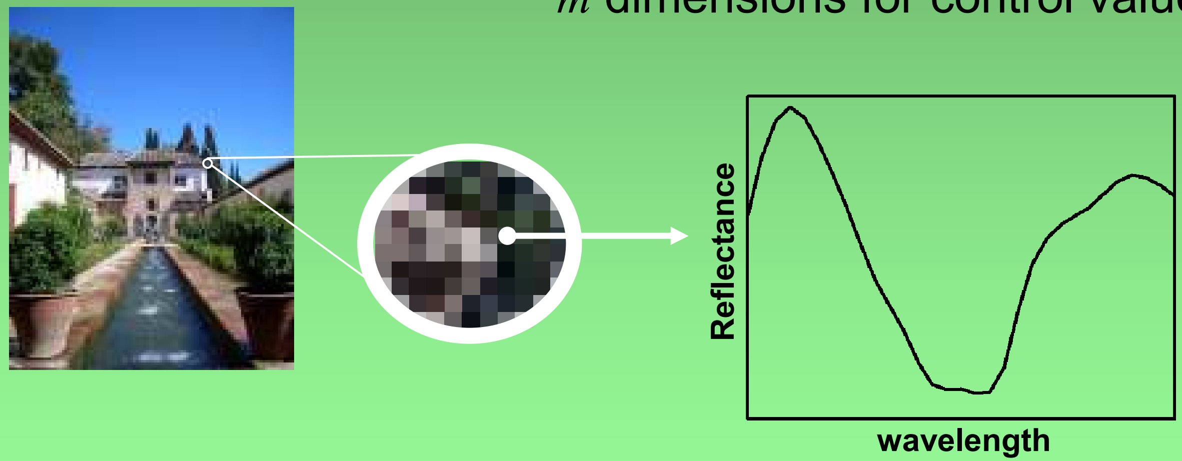
Motivation and Problems

Problems:

- Non linear printer behavior



- High dimensionality: 31 dimensions for spectra
  m dimensions for control values (e.g. m = 6,7)

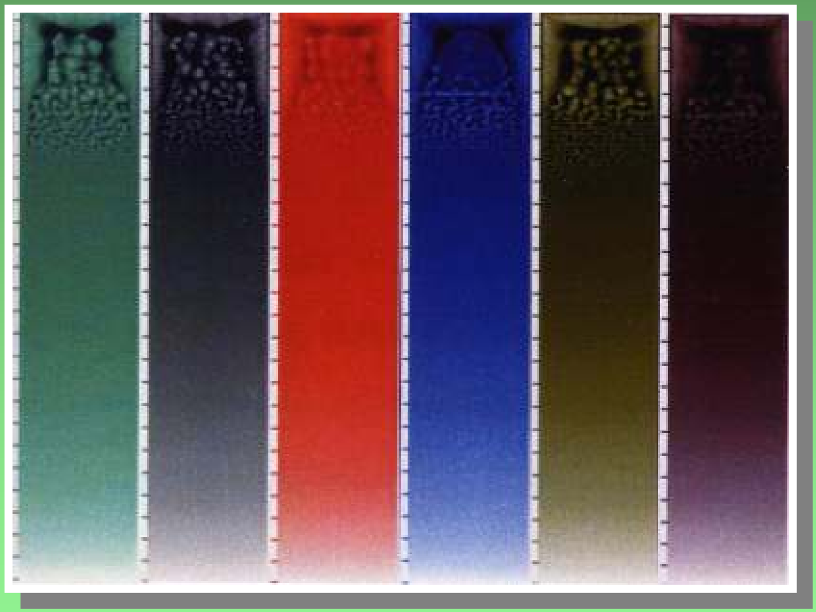


Separation on a Pixel by Pixel Basis $\Rightarrow$ very fast algorithm and implementation

Motivation and Problems

Problems:

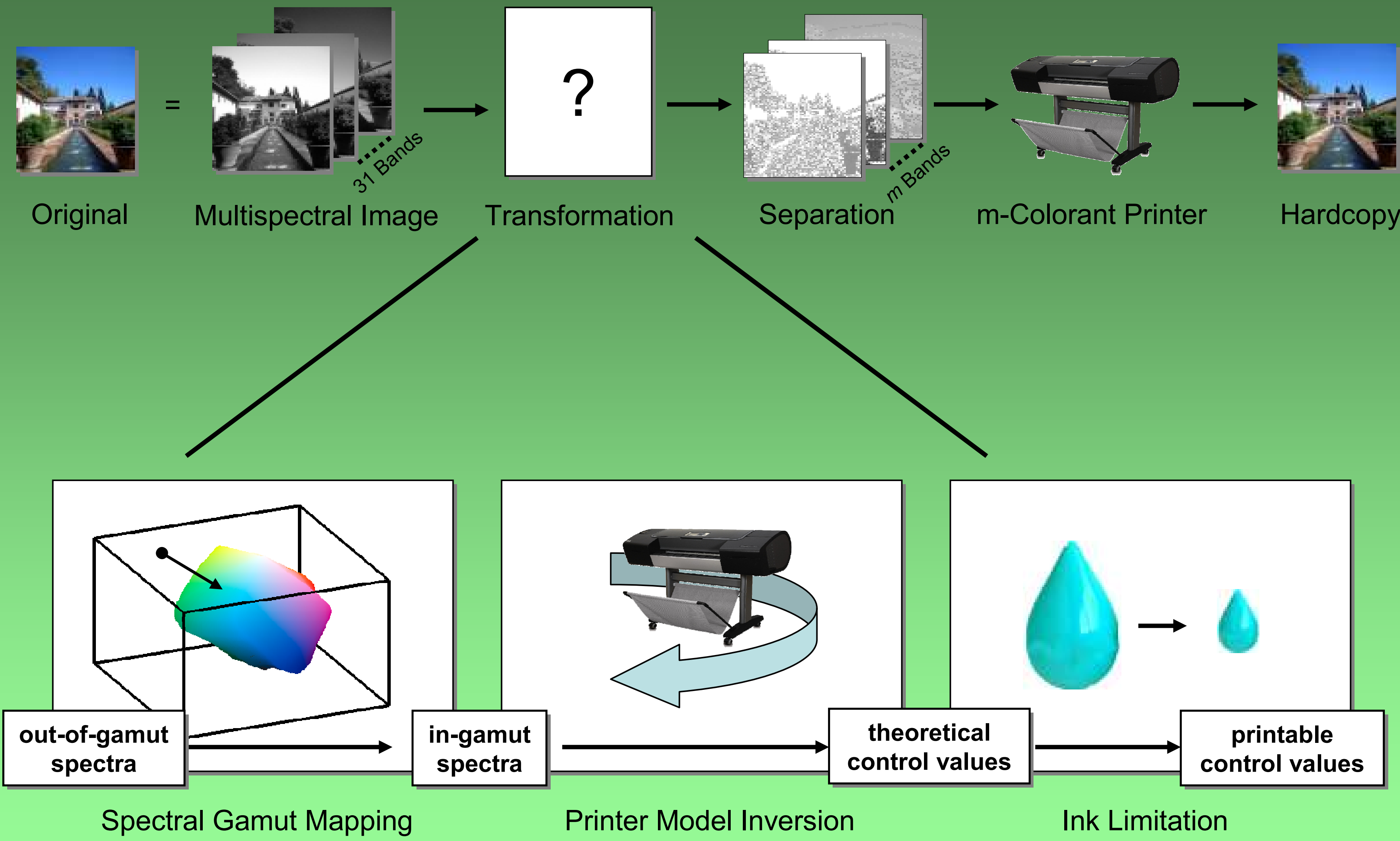
- Limited physical colorant-absorbtion of media $\Rightarrow$ ink limitation necessary



Secondary and tertiary colors

Multispectral-Printing Workflow

Workflow

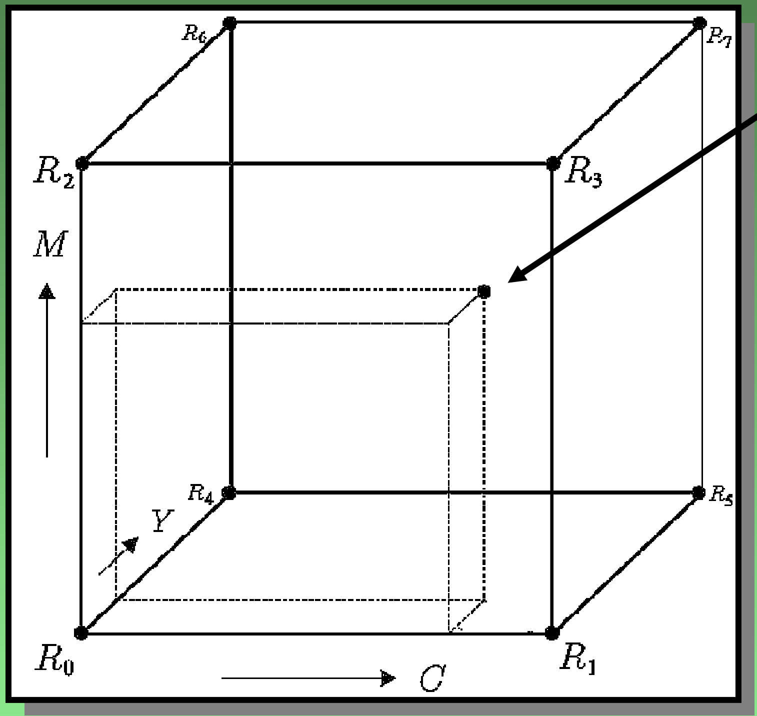

=
31 Bands
?
m Bands
Original
Multispectral Image
Transformation
Separation
m-Colorant Printer
Hardcopy
out-of-gamut spectra
in-gamut spectra
theoretical control values
printable control values
Spectral Gamut Mapping
Printer Model Inversion
Ink Limitation

The Printer Model

The Cellular Yule-Nielsen Spectral Neugebauer (CYNSN) Model

The Cellular Yule-Nielsen Spectral Neugebauer (CYNSN) Model

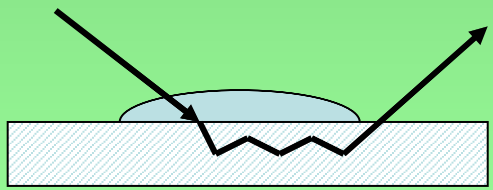
The plain Yule-Nielsen Spectral Neugebauer (YNSN) model:



$$R(C,M,Y) = \left[\sum_{i=0}^{7} a_i(C,M,Y) R_i^{1/n}\right]^n$$

Demichel equations:

$$\begin{aligned}
a_0(C,M,Y) &= (1-c)(1-m)(1-y) \\
a_1(C,M,Y) &= c(1-m)(1-y) \\
a_2(C,M,Y) &= (1-c)m(1-y) \\
a_3(C,M,Y) &= c\,m(1-y) \\
a_4(C,M,Y) &= (1-c)(1-m)y \\
a_5(C,M,Y) &= c(1-m)y \\
a_6(C,M,Y) &= (1-c)m\,y \\
a_7(C,M,Y) &= c\,m\,y
\end{aligned}$$



Optical dot gain (n -factor)

$R_i \equiv$ Neugebauer primaries

$c(C), m(M), y(Y) \equiv$ effective area coverages

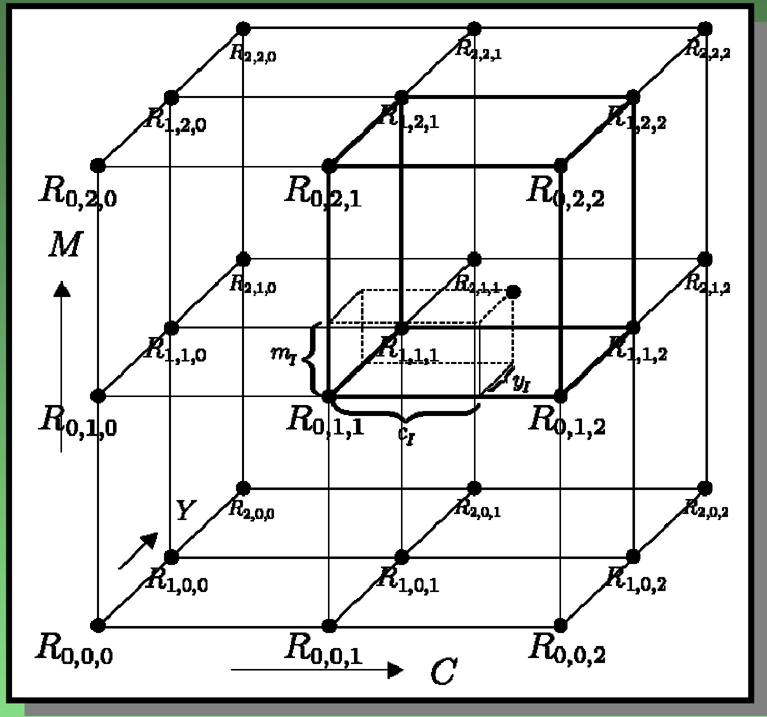
The Cellular Yule-Nielsen Spectral Neugebauer (CYNSN) Model

- Subdivision of the colorant space into smaller cells

- Each cell contains a YNSN model with cell primaries instead of Neugebauer primaries

$$R(C,M,Y) = \left[\sum_{i=0}^{7} a_{I_i}(C,M,Y) R_{I_i}^{1/n}\right]^n$$

$$\begin{array}{ll} I_0 = I + (0,0,0) & I_1 = I + (0,0,1) \\ I_2 = I + (0,1,0) & I_3 = I + (0,1,1) \\ I_4 = I + (1,0,0) & I_5 = I + (1,0,1) \\ I_6 = I + (1,1,0) & I_7 = I + (1,1,1) \end{array}$$

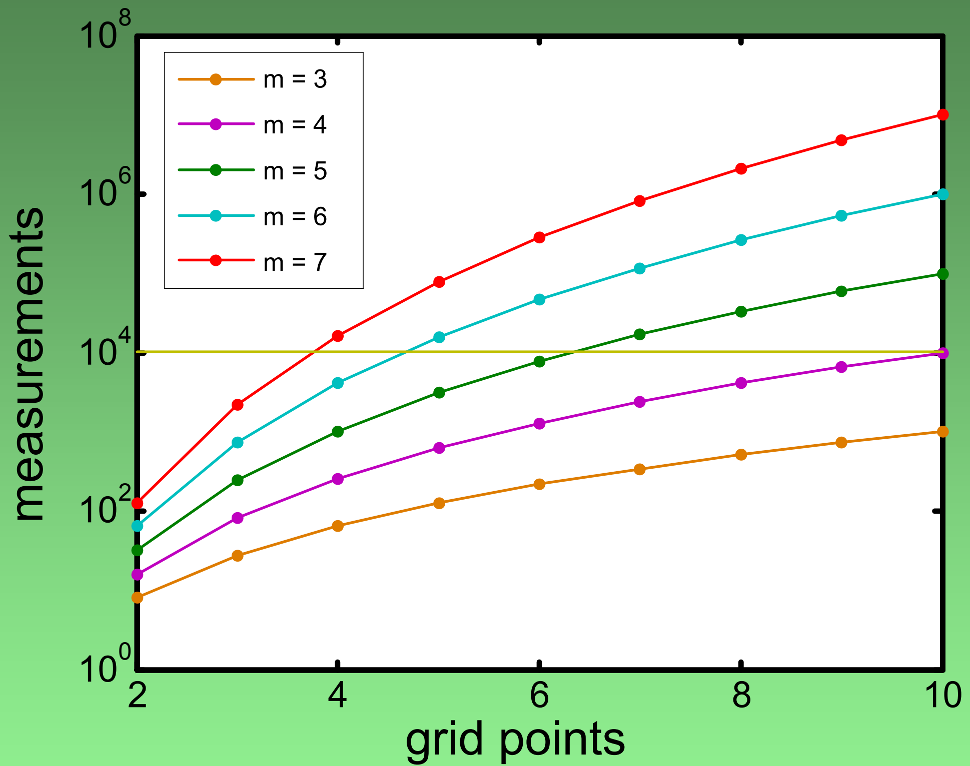


- Normalized effective area coverages to the cell primaries $v_{I_i} = \left[v_{I_i}^C, v_{I_i}^M, v_{I_i}^Y\right]$

$$\begin{aligned} c_I &= (v_{I_7}^C - C)/(v_{I_7}^C - v_{I_0}^C) \\ m_I &= (v_{I_7}^M - M)/(v_{I_7}^M - v_{I_0}^M) \\ y_I &= (v_{I_7}^Y - Y)/(v_{I_7}^Y - v_{I_0}^Y) \end{aligned}$$

The Cellular Yule-Nielsen Spectral Neugebauer (CYNSN) Model

- *k* grid points in each dimension result in $(k-1)^m$ cells and k^m measurements



$\Rightarrow$ Tradeoff between model accuracy and measurement effort

Spectral Gamut Mapping

Spectral Gamut Mapping

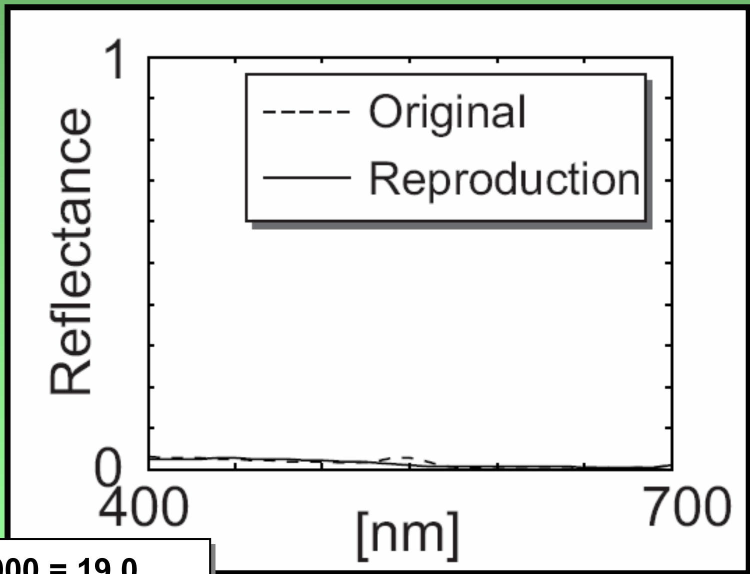
- Minimizing spectral root mean square (RMS) error:

$$\text{minimize} \quad \left\| R(\psi) - r \right\|_2 = \min$$

$$\text{subject to} \quad \psi \in [0,1]^m$$

$R(\psi)$ - printer model, e.g. CYNSN
ψ - control values, e.g. CMYKRGB
r - given reflectance spectrum

- Problem: colorimetric error does not correlation well with spectral RMS error (especially dark colors)



CIEDE2000 = 19.0
spectral RMS = 0.031

Spectral Gamut Mapping

- Spectral Gamut mapping better related to human color vision:

  If the CIEXYZ colors of a surface are known for enough illuminants the reflectance spectrum can be reconstructed from these colors

$$r = \Omega^{\ominus} \cdot \begin{bmatrix} X_{L1} \\ Y_{L1} \\ Z_{L1} \\ \vdots \\ X_{Lq} \\ Y_{Lq} \\ Z_{Lq} \end{bmatrix} \qquad \Omega = \begin{bmatrix} \bar{x}(\lambda_1)L1(\lambda_1) & \cdots & \bar{x}(\lambda_N)L1(\lambda_N) \\ \bar{y}(\lambda_1)L1(\lambda_1) & \cdots & \bar{y}(\lambda_N)L1(\lambda_N) \\ \bar{z}(\lambda_1)L1(\lambda_1) & \cdots & \bar{z}(\lambda_N)L1(\lambda_N) \\ \vdots & & \vdots \\ \bar{x}(\lambda_1)Lq(\lambda_1) & \cdots & \bar{x}(\lambda_N)Lq(\lambda_N) \\ \bar{y}(\lambda_1)Lq(\lambda_1) & \cdots & \bar{y}(\lambda_N)Lq(\lambda_N) \\ \bar{z}(\lambda_1)Lq(\lambda_1) & \cdots & \bar{z}(\lambda_N)Lq(\lambda_N) \end{bmatrix}$$

$(X_{Li}, Y_{Li}, Z_{Li})^T$ - tristimuli under illuminant i

Li - SPD of illuminant i

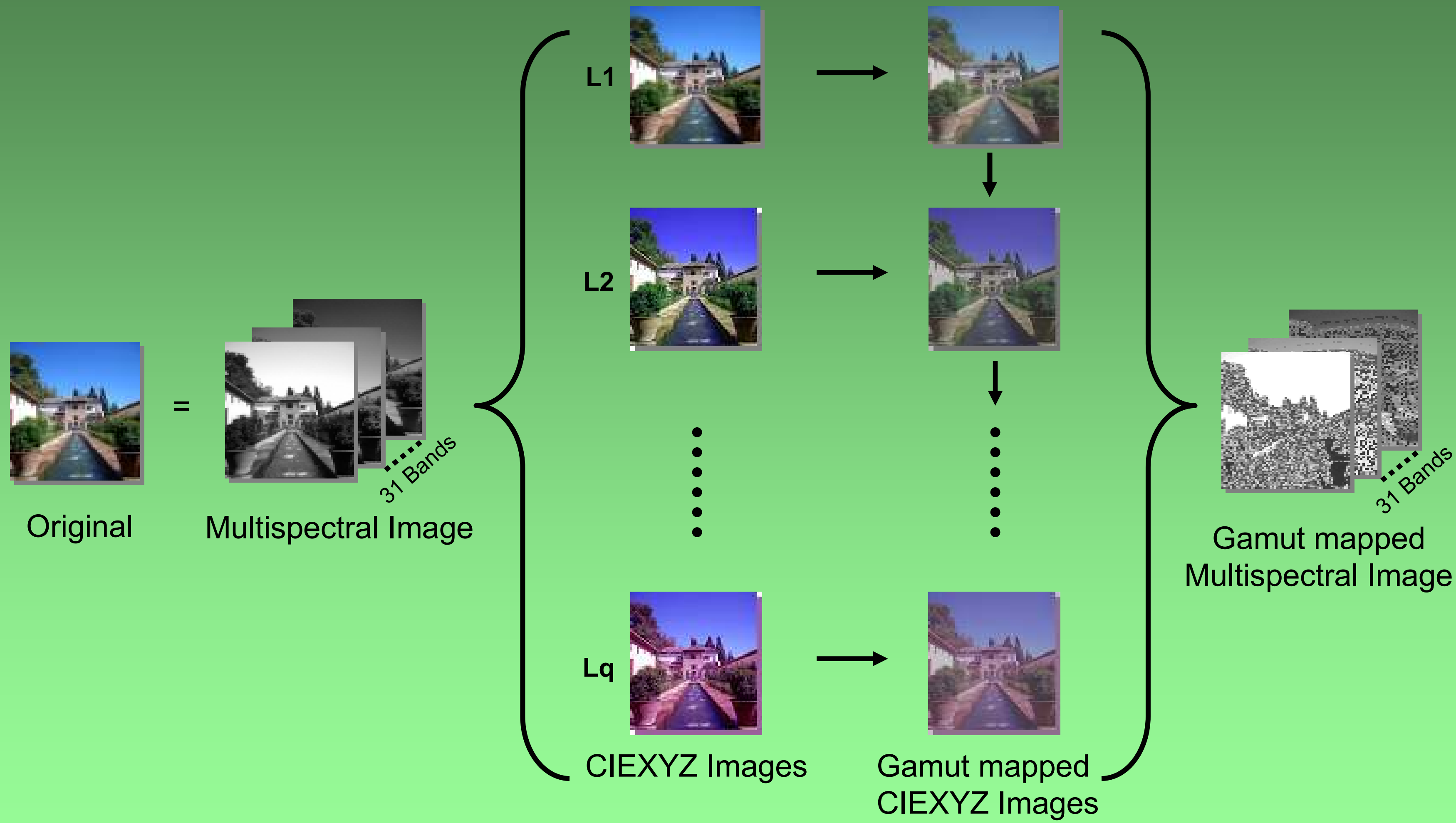
$\bar{x}, \bar{y}, \bar{z}$ - color matching functions

Ω - lighting matrix

$\Omega^{\ominus}$- pseudoinverse of the lighting matrix

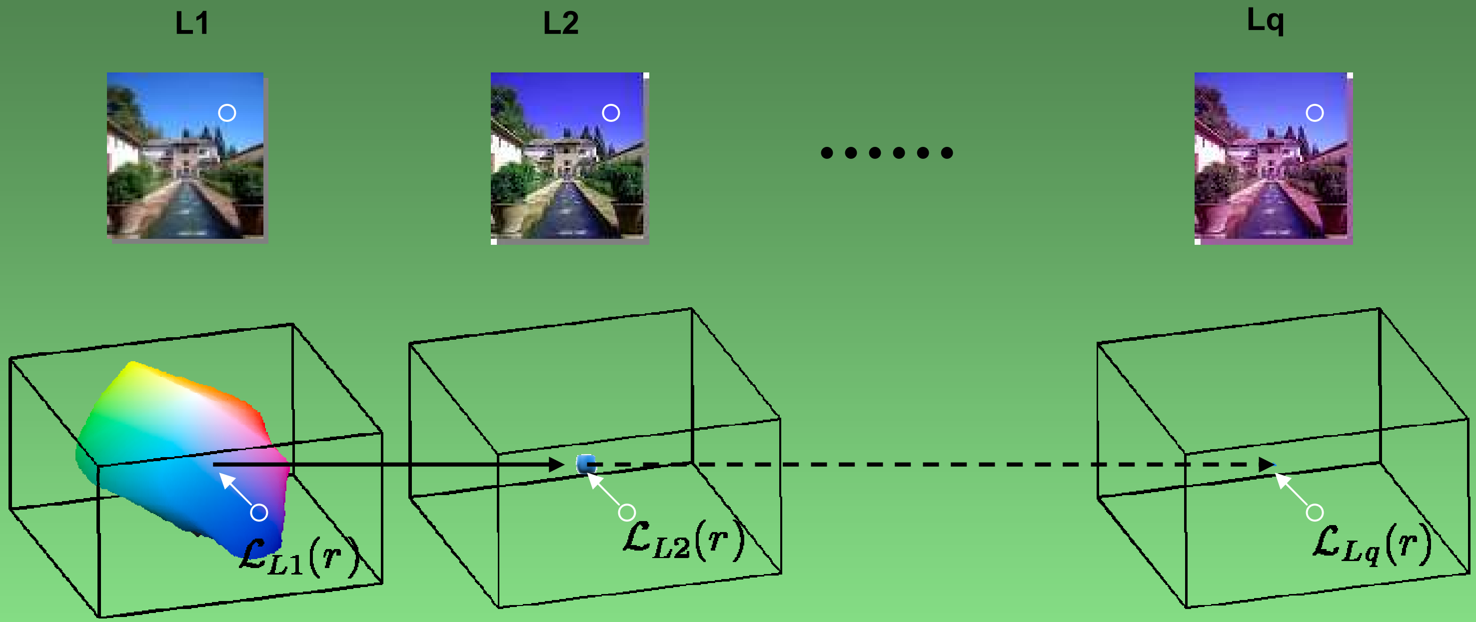
Spectral Gamut Mapping

- Reproduction has to match the given reflectance under a set of illuminants



Spectral Gamut Mapping

- Metamer mismatch-based spectral gamut mapping

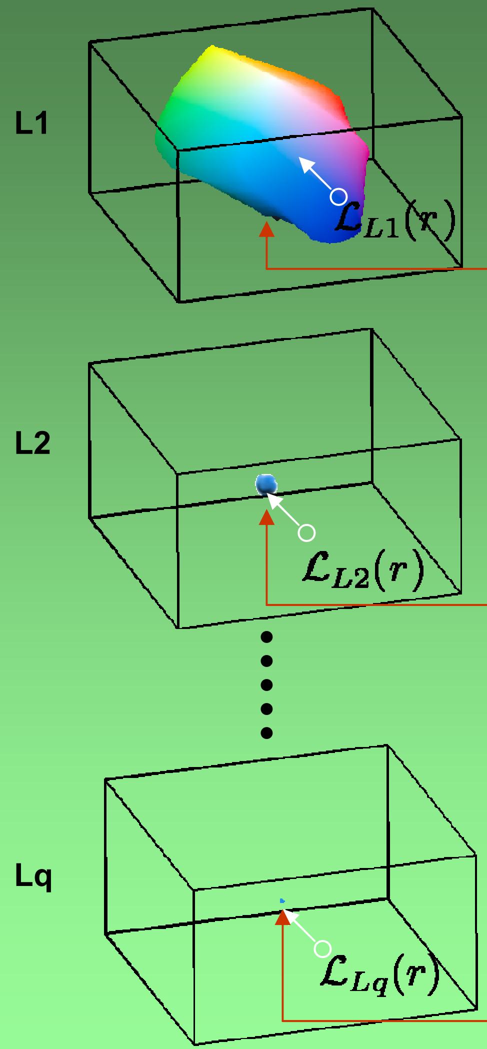


traditional gamut mapping onto gamut	gamut mapping onto the printer's metamer mismatch gamut	gamut mapping onto the printer's metamer mismatch gamut
$\mathcal{L}_{L1}(R(\Psi))$	$\mathcal{L}_{L2}(M_{L1}(x_{L1}(r)) \cap R(\Psi))$	$\mathcal{L}_{Lq}\left(\bigcap_{L=L1}^{L(q-1)} M_L(x_L(r)) \cap R(\Psi)\right)$

$\Psi = [0,1]^m$ $M_{Li}(x_{Li}(r))$ = Set of all metameric reflectances for $x_{Li}(r)$ under illuminant Li

Spectral Gamut Mapping

- Metamer mismatch-based spectral gamut mapping



$$x_{L1}(r) = G_{\text{Trad}}(\mathcal{L}_{L1}(R(\Psi)), \mathcal{L}_{L1}(r))$$

$$x_{L2}(r) = g(\mathcal{L}_{L2}(M_{L1}(x_{L1}(r)) \cap R(\Psi)), \mathcal{L}_{L2}(r))$$

$$x_{Lq}(r) = g(\mathcal{L}_{Lq}(\bigcap_{L=L1}^{L(q-1)} M_L(x_L(r)) \cap R(\Psi)), \mathcal{L}_{Lq}(r))$$

G_{Trad} - Traditional gamut mapping

g - Metamer mismatch gamut mapping e.g. min ΔE^*_{00}

Inversion of the CYNSN model

The Linear Regression Iteration (LRI) Method

- Use a special property of the YNSN model:

  The YNSN model is multilinear in *1/n*-space, i.e.

$$R(\psi)^{1/n} = \vec{A}_i(\psi) \cdot \psi_i + \vec{B}_i(\psi)$$

  for each colorant ψ_i .

  $\vec{A}_i(\psi)$, $\vec{B}_i(\psi)$ are independent of ψ_i .

- Set the model equal to the given reflectance *r* in *1/n*-space

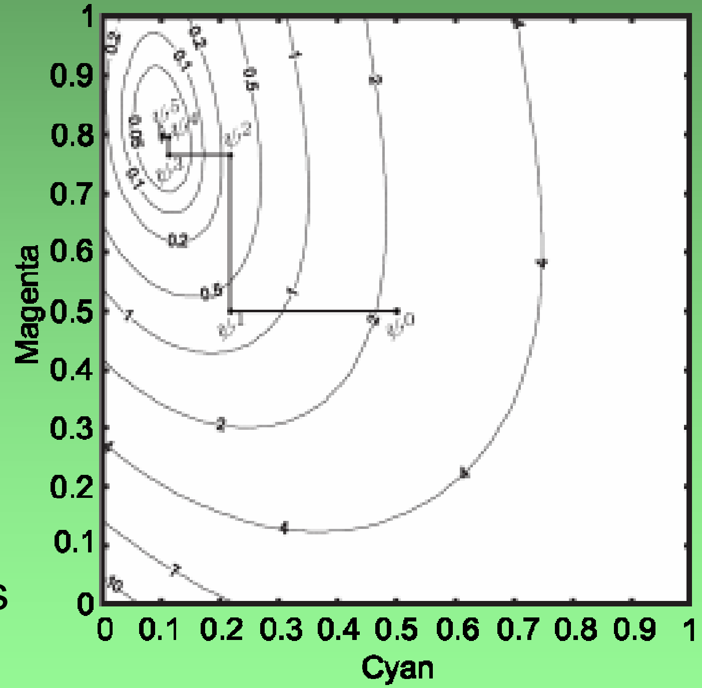
$$\begin{aligned}
\vec{A}_i(\psi)\psi_i + \vec{B}_i(\psi) &= \vec{r}^{\frac{1}{n}} \\
\Leftrightarrow \quad \vec{A}_i(\psi)\psi_i &= \vec{r}^{\frac{1}{n}} - \vec{B}_i(\psi) \\
\Rightarrow \quad \vec{A}_i(\psi)^T \vec{A}_i(\psi)\psi_i &= \vec{A}_i(\psi)^T(\vec{r}^{\frac{1}{n}} - \vec{B}_i(\psi)) \\
\Rightarrow \quad \psi_i^{\min} &= \frac{\vec{A}_i(\psi)^T(\vec{r}^{\frac{1}{n}} - \vec{B}_i(\psi))}{\vec{A}_i(\psi)^T \vec{A}_i(\psi)}
\end{aligned}$$

The Linear Regression Iteration (LRI) Method

- Iterating the linear regressions for each colorant result in the Linear Regression Iteration (LRI) method

1. REPEAT {
2. FOR $(i=1;\ i \leq m;\ i=i+1)$ {
3. $\psi_i = D\left[\frac{\vec{A}_i(\psi)^T(\vec{B}_i(\psi)-r^{1/n})}{\vec{A}_i(\psi)^T\vec{A}_i(\psi)}\right]$;
4. }
5. } UNTIL TERMINATION;

with $D[x] = \begin{cases} 0, & x < 0 \\ 1, & x > 1 \\ x, & \text{otherwise} \end{cases}$

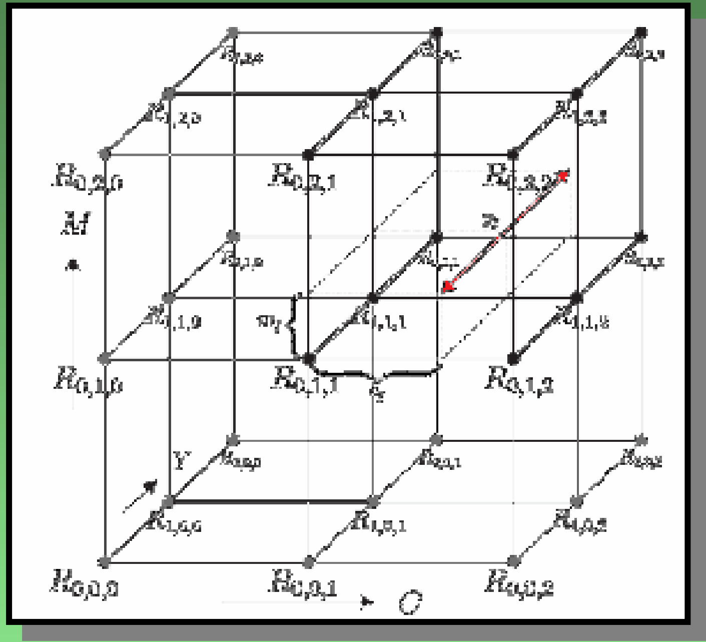


- Descent directions are along the colorant axes
- Perfect step length

Expansion of the LRI Method to the CYNSN Model

Main idea:

- Descent direction still along colorant axes
- Find optimal step length using linear regression in all cells along the descent direction



k grid points in each dimension

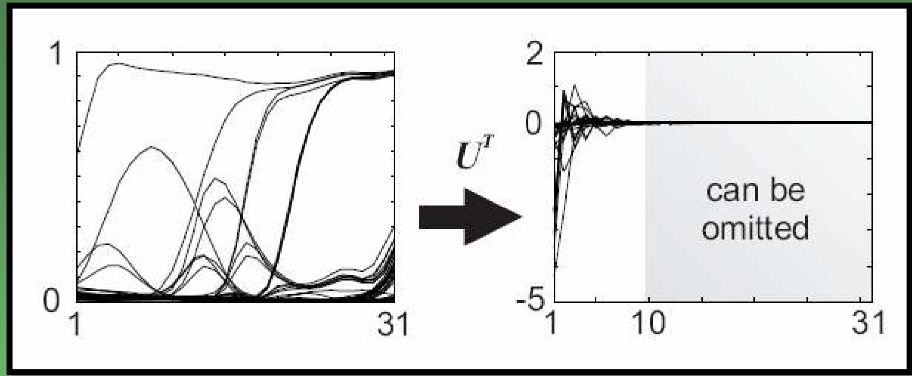
→ k-1 cells

→ max. k-1 linear regressions

Acceleration of the CLRI Method on the Neugebauer Subspace

Main idea:

- Singular Value Decomposition of all cell primary reflectances



$$\mathbf{R}_{\text{Cell}}^{1/n} = U \cdot S \cdot V^T$$

U is orthonormal i.e. length preserving

- Reducing dimensions by using only *k* columns of U

$$\begin{aligned} U_k^T R^{1/n}(\psi) &= U_k^T r^{1/n} \\ \Leftrightarrow \quad U_k^T \vec{A}_i(\psi)\psi_i + U_k^T \vec{B}_i(\psi) &= U_k^T r^{1/n} \\ \Rightarrow \quad \psi_i^{\min} &= \frac{(U_k^T \vec{A}_i(\psi))^T (U_k^T r^{1/n} - U_k^T \vec{B}_i(\psi))}{(U_k^T \vec{A}_i(\psi))^T U_k^T \vec{A}_i(\psi)} \end{aligned}$$

Ink Limitation

Ink Limitation

Main idea:

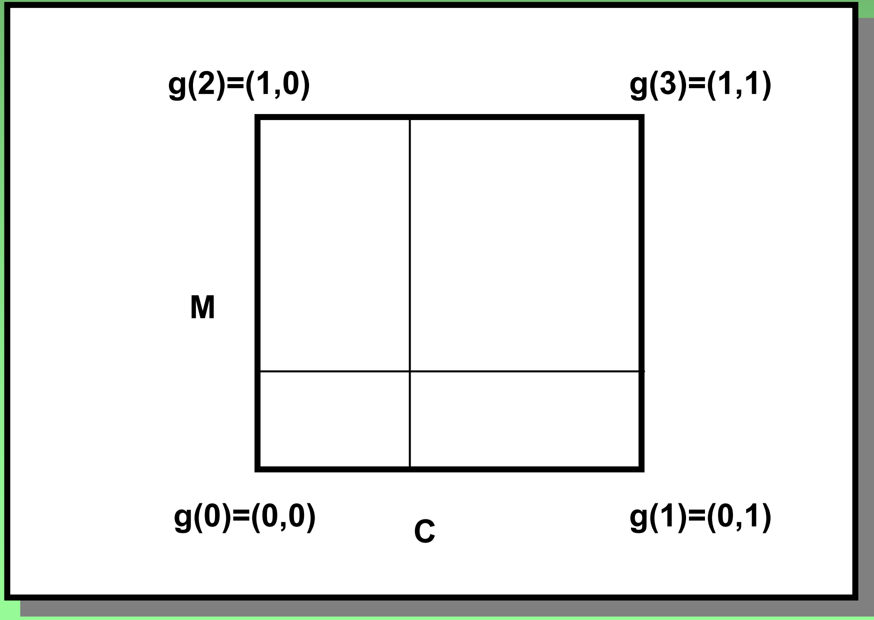
- Determine the max. ink coverage f_{MAX}
- Ink limitation function (multilinear interpolation):

$$\psi \rightarrow \sum_{i=0}^{2^m-1} a_i(\psi) \frac{\min(f_{\mathrm{MAX}}, \|g(i)\|_1)}{\|g(i)\|_1} g(i)$$

where

$$g(i) = (x_0, \ldots, x_{m-1})^T$$

$$i = \sum_{j=0}^{2^m-1} x_j 2^j$$



- CYNSN-model target has to be printed using this ink-limitation

Results

Results

Demonstrator system:

- RIP: Onyx ProductionHouse RIP, Version 7
- Printer: HP Designjet Z3100 Photo
  Ink set: CMYKRGB
  CYNSN model with 4-gridpoints
  Yule-Nielsen *n*-factor = 10
- Paper: Proofing paper, Felix-Schoeller (H74261) 270g/m²

Results

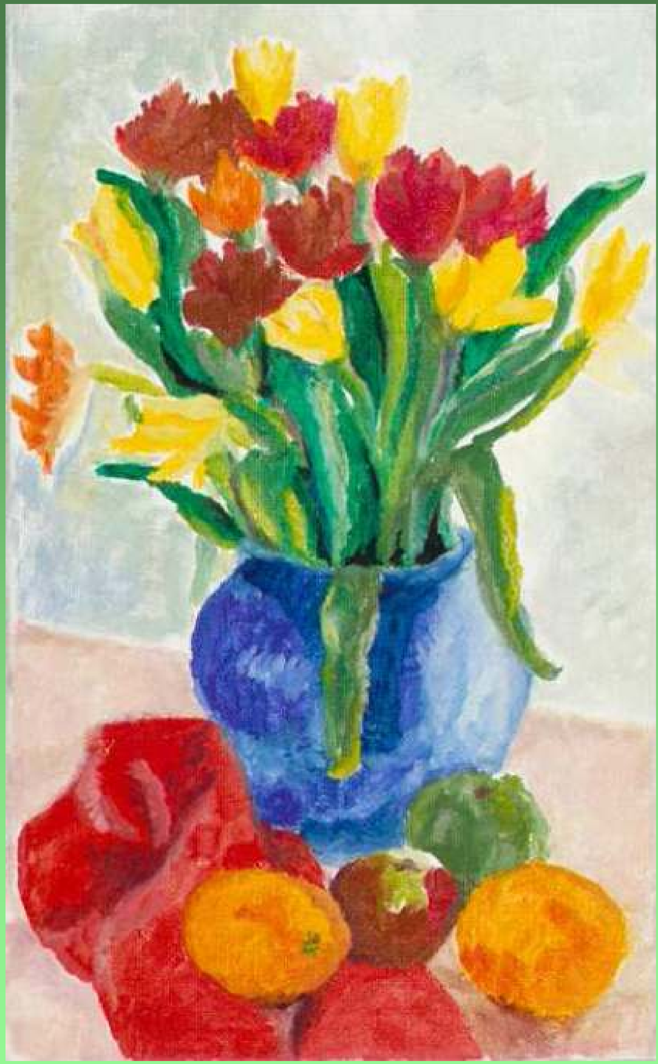
- Reproduction of 35 color paint samples:

	$\Delta E_{00}[D65]$	$\Delta E_{00}[A]$	$(\Delta E_{00}[D65]+\Delta E_{00}[A])/2$
mean	2.17	1.75	1.96
std	0.52	0.62	0.48
max	3.25	3.27	2.80

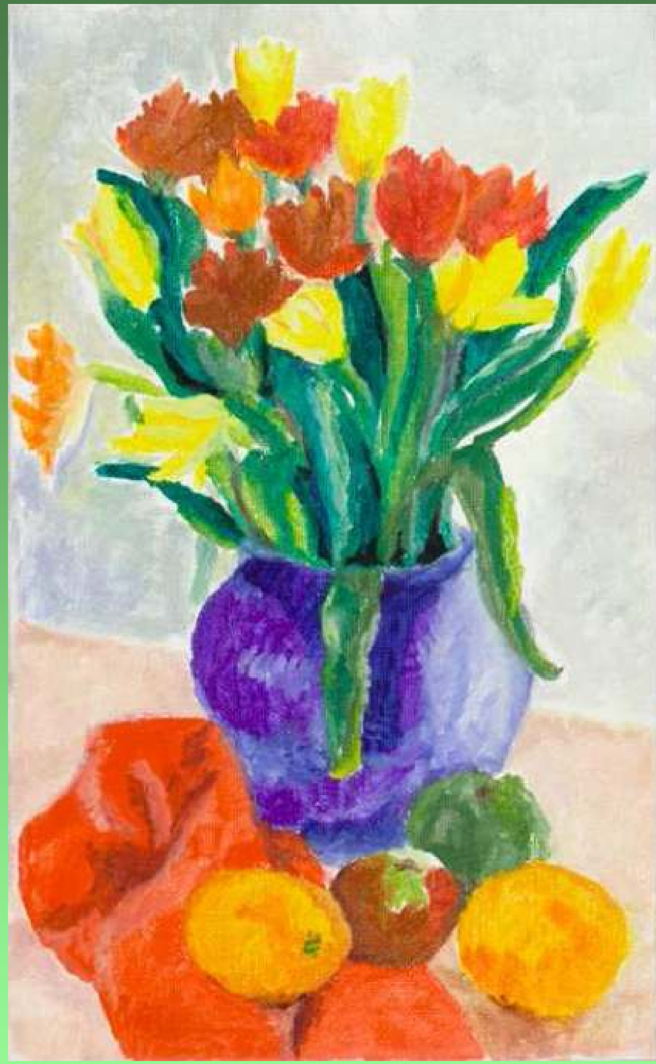
- Reproduction of different paintings

  5 mega-pixel paintings - separation duration 4 minutes (Intel Q6600)
  25 mega-pixel Metacow - separation duration 3 minutes (Intel Q6600)

Results



Daylight (CIE D65)



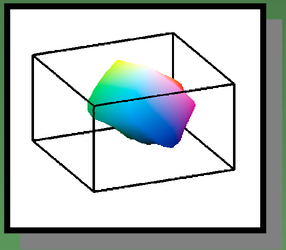
Incandescent light (CIE A)

Results

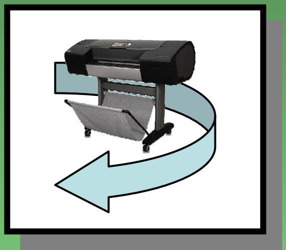
Daylight (CIE D65)

Incandescent light (CIE A)

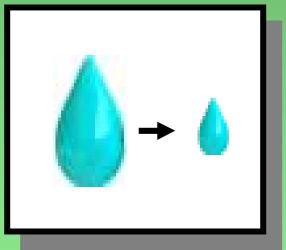
Conclusion



- Metamer mismatch-based spectral gamut mapping
  → Reproduction has to match the given reflectance under a set of illuminants



- CYNSN model inversion
  → Inversion based on Iterating linear regressions
  → Expanding to multiple cells
  → Acceleration using subspace approach



- Ink-limitation using multilinear-interpolation

- Reproducing patches, paintings and metameric targets

Acknowledgments

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ONYX

hp invent

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