Přednáška 06

Komprese a modelování rozsáhlých obrazových dat

Efektivní reprezentace BTF dat

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Outline – Dimensionality and Compression

- BTF data dimensionality analysis
  - SVD, PCA & psychophysical methods
- Methods of BTF data compression
  - PCA Eigen-images
  - Reflectance models
  - SVD tensors
  - Spherical harmonics + wavelets
  - Data clustering
  - Layered volumetric models
  - Vector quantization
- Selected methods comparison

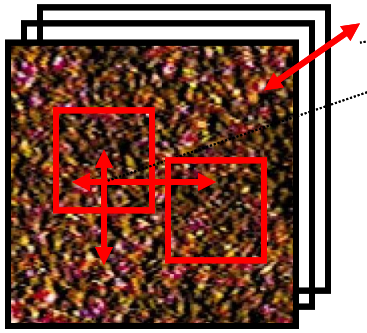
BTF Sample Dimensionality Analysis

[Suen & Healey, IEEE PAMI 2000]

SVD of BTF data correlations

- Sample complexity ~ Dimensionality ⇨ Number of highest eigen-values of correlation between RGB components in moving support window (for each combination of view and illumination directions).
- Tested on CURET database only.

ij = RR, RG, RB, GR, …



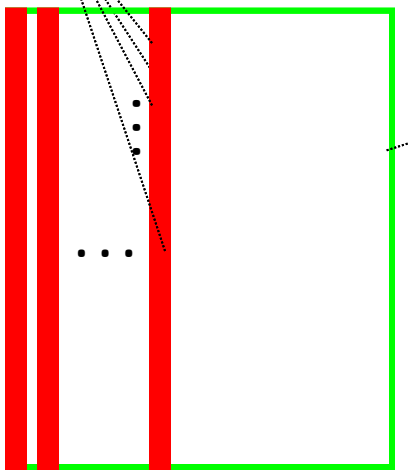
No of correlations

$$R_{ij}(\mathbf{m}) = \frac{1}{|\Lambda(\mathbf{m})|} \sum_{\mathbf{x}\in\Lambda,(\mathbf{x}+\mathbf{m})\in\Lambda} [I_i(\mathbf{x}) - \bar{I}_i][I_j(\mathbf{x}+\mathbf{m}) - \bar{I}_j]$$

$$\bar{I}_i = \frac{1}{|\Lambda|} \sum_{\mathbf{x}\in\Lambda} I_i(\mathbf{x})$$

$$\mathbf{R} = \mathbf{U}\mathbf{D}\mathbf{V}^T$$

$$\mathbf{x} = [r_1, r_2]^T$$



No of BTF images

$$\frac{\sum_{i=1}^{\mathcal{D}} \sigma_i^2}{\sum_{i=1}^{n_i n_v} \sigma_i^2} \geq F$$

Typical values 5-15 ($F = 0.99$)

BTF Sample Dimensionality Analysis

[Koudelka et al. TEXTURE 2003]

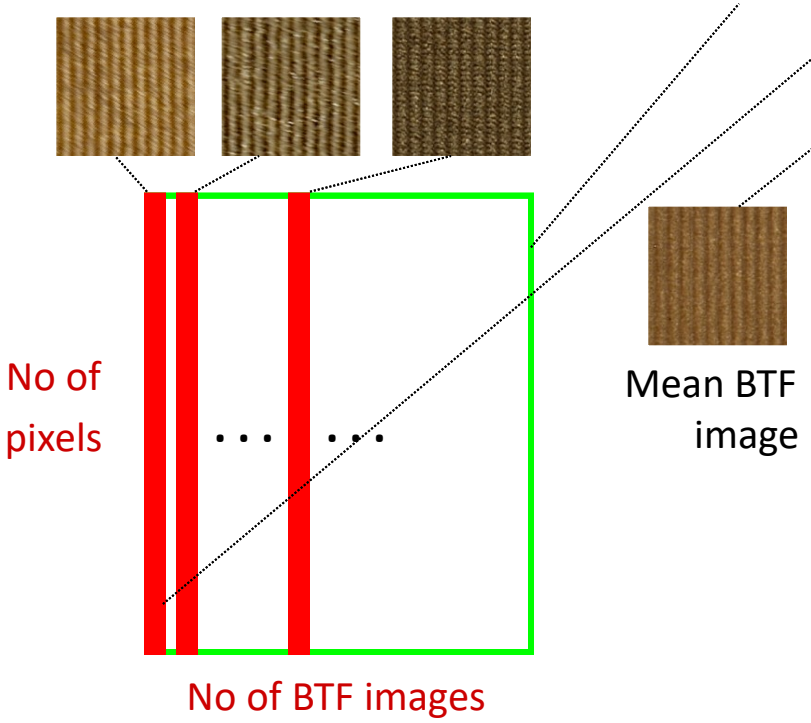
PCA of BTF data

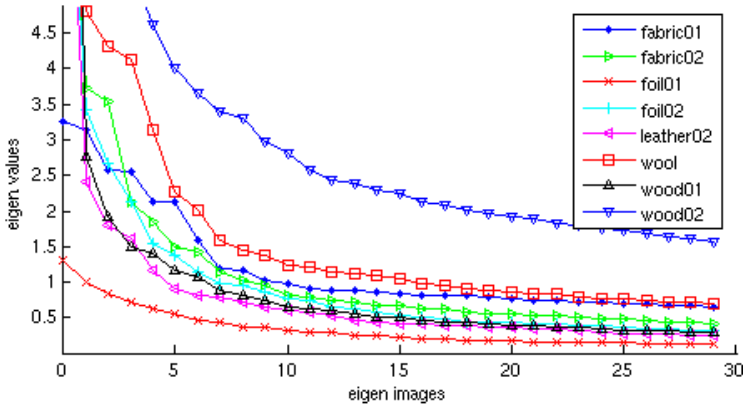
- Dimensionality ⇨ number of eigen-images with the highest energy
- Typical value 30 ($F = 0.9$)

$$\mathbf{A} = [\mathbf{X}_1 - \hat{\mathbf{X}}, \mathbf{X}_2 - \hat{\mathbf{X}}, \ldots, \mathbf{X}_{n_i \cdot n_v} - \hat{\mathbf{X}}]$$

$$\mathbf{M} = \mathbf{A}^T \mathbf{A}$$

$$\mathbf{M} = \mathbf{U}\mathbf{D}\mathbf{V}^T \rightarrow \frac{\sum_{i=1}^{\mathcal{D}} \sigma_i^2}{\sum_{i=1}^{n_i n_v} \sigma_i^2} \geq F$$





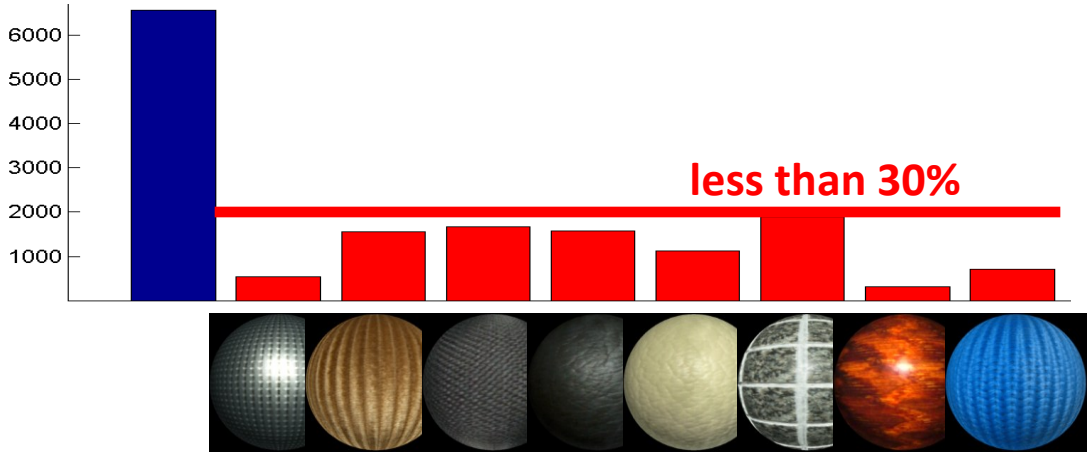
BTF Sample Dimensionality Analysis

[Filip et al. ACM TOG 2008]

Psychophysical estimation of BTF dimensionality

- Pixel-wise difference of image pairs (SSIM, VDP, CIE LAB, etc.)
- Similar images substituted by representative one
- Selection of important BTF images only
- **BTF index map**:
  - Substituted images (index only)
  - Preserved BTF images

#■ >>#■





Selected subset:

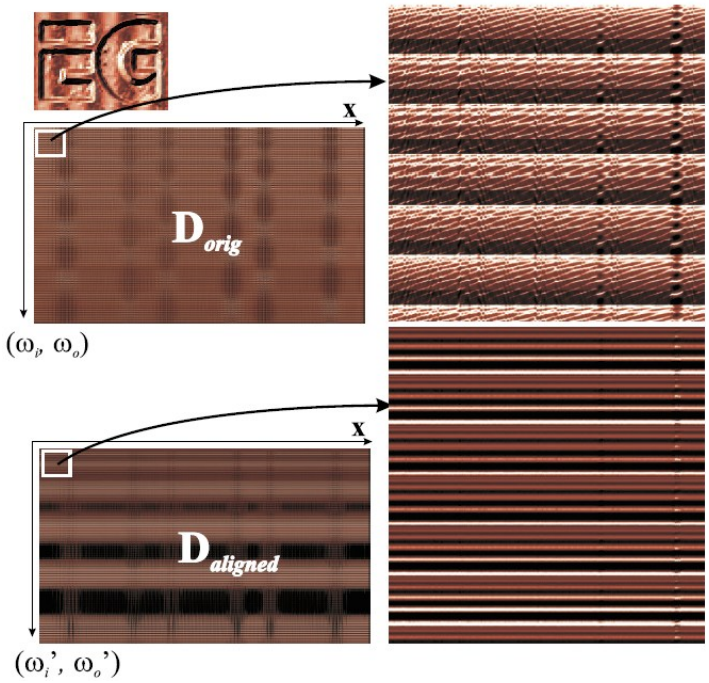
5-30% of original images

BTF Data Alignment Dimensionality Reduction

[Müller et al. 06] – BTF variance reduction by data alignment with respect to a local geometry.

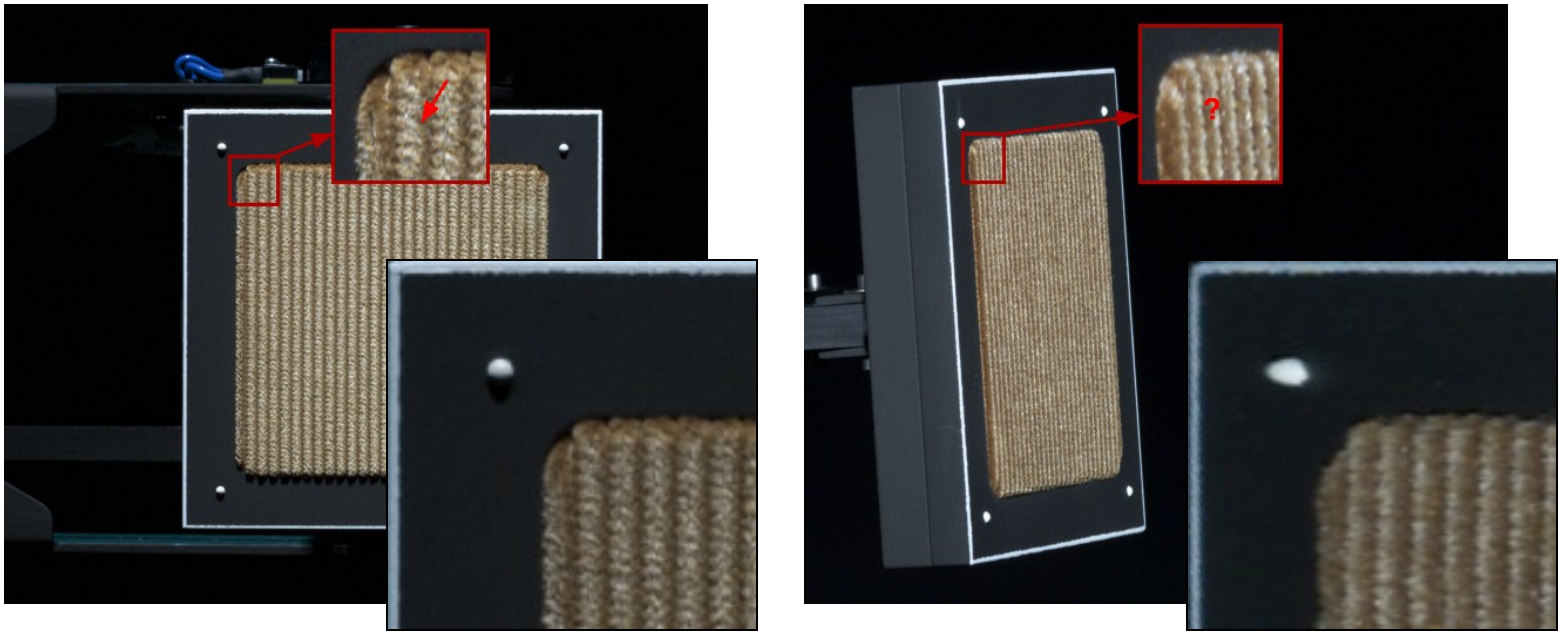
- Estimate per-pixel coordinate system maximizing ABRDFs correlation ⇨ rotations of ABRDFs.
- Maximization ⇨ ABRDFs represented by spherical harmonics in Fourier space.
- Variance reduction ⇨ higher compression

[Müller et al. 06]



Compression Methods

- Compression of all BTF images at once ($BTF(r_1, r_2, i, v)$)



Courtesy of University of Bonn

- Compress individual views (reflectance fields $\mathcal{R}_v(r_1, r_2, i)$) separately

Compression Methods Taxonomy

- Compression of all BTF images at once
  - ABRDF factorization
  - Fitting BRDF models to pixel-wise ABRDFs
  - Full BTF factorization
  - Per-cluster factorization
  - ABRDFs clustering + clusters compression (SVD,BRDF model)
- Compression of separate views (reflectance fields)
  - Fitting BRDF models to a fixed view ABRDF data
  - Per-view factorization
- Combining geometrical and reflectance information
- Multi-level vector quantization
- Mixture of parametric BRDF models

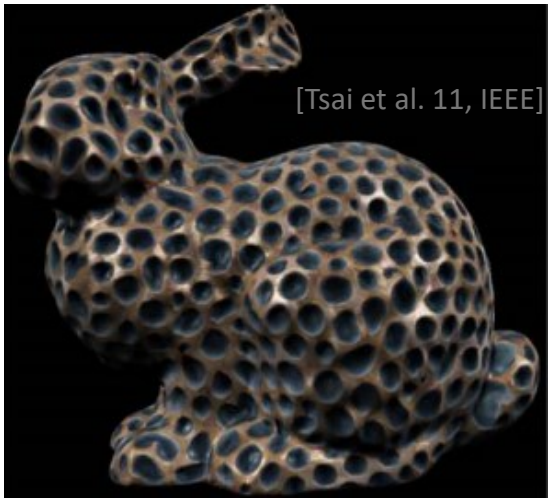
ABRDF Factorization

[Tsai et al. 11 PAMI] – ABRDF as multivariate spherical radial basis functions

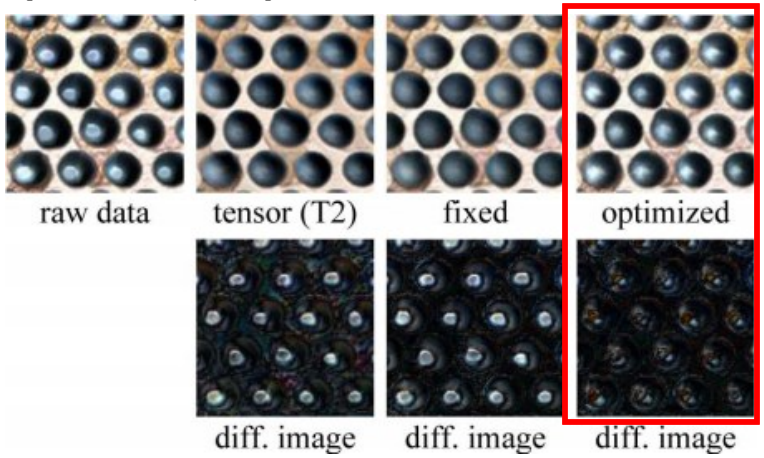
$$BRDF(\omega_i, \omega_v) = \sum_{j=1}^{J} \beta_j \prod_{n=1}^{3} e^{\lambda_{j,n} \cdot \psi_n(\omega_i, \omega_v | \theta_n) - \lambda_{j,n}}$$

☑ good compression, data-dependent, continuous param. rep.

☒ Slower fitting, lower compression ratios than linear factorization methods



[Tsai et al. 11, IEEE]



Fitting BRDF Reflectance Models

[McAlister 02] – fitting pixel-wise single multi-lobe Lafortune model (LM) to all view and illum. directions

$$BTF(r_1, r_2, i, v) \approx \rho_{d,r_1,r_2} + \sum_{k}^{n_l} \rho_{s,r_1,r_2,k} [\omega_i^T \mathbf{D}_{r_1,r_2,k} \omega_v]^{n_{r_1,r_2,k}}$$

[McAllister 02]



☑ good compression, fast fitting

☒ blurry images, suitable for low-height samples only

[Daubert 01] – LM + additional iteratively obtained look-up table

$$BTF(r_1, r_2, i, v) \approx T_{\omega_v,r_1,r_2} \left(\rho_{d,r_1,r_2} + \sum_{k}^{n_l} [\omega_i^T \mathbf{D}_{r_1,r_2,k} \omega_v]^{n_{r_1,r_2,k}} \right)$$

☑ good quality for regular samples

☒ require to store extensive view-dependent look-up table

[Daubert 01]

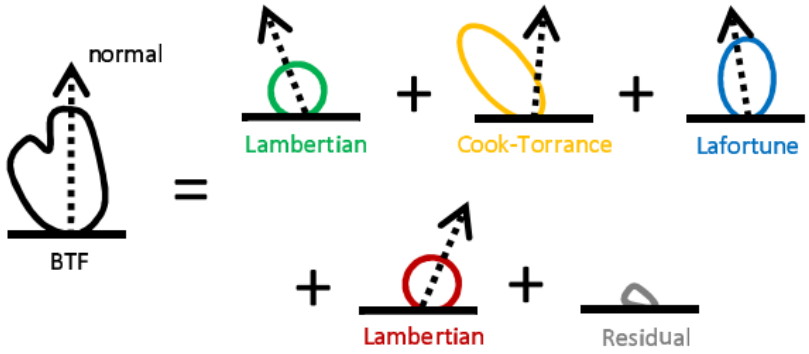


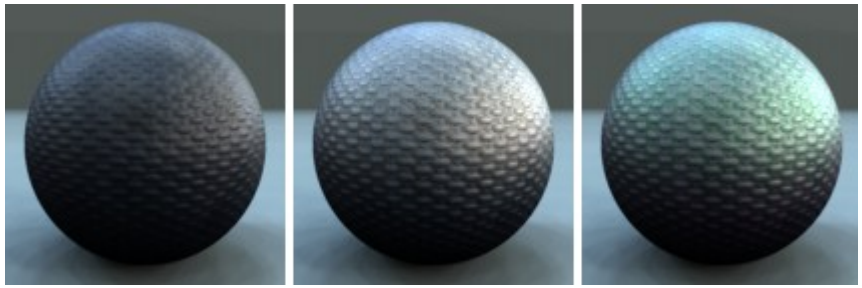
[Wu et al. 11 EG] – each BTF texel as mixture of weighted sparse parametric BRDF models.

- Straightforward appearance (spatial, reflectance) editing by parameters modifications.

☑ high compression, $\approx \frac{1}{300}$ parametric editing, importance sampling support

☒ time demanding compression, no GPU implementation





[Wu et al. 11, JW]

Fitting Per-View BRDF Reflectance Models

[Malzbender 01] – each view direction represented by per-pixel polynomials.

$$\mathcal{R}_v(r_1, r_2, i) \approx a_o(r_1, r_2)u_{r_1}^2 + a_1(r_1, r_2)u_{r_2}^2 + a_2(r_1, r_2)u_{r_1}u_{r_2} + \\ + a_3(r_1, r_2)u_{r_1} + a_4(r_1, r_2)u_{r_2} + a_5(r_1, r_2)$$

☑ fast fitting

☒ low quality, not suitable for specular materials



[Malzbender 01]

Fitting Per-View BRDF Reflectance Models


[Meseth et al. 03]

[Meseth et al. 03] – Colour albedo-map modulated by a luminance Lafortune model (up to 3 lobes)

☑ less parameters to store

☒ for less specular samples only

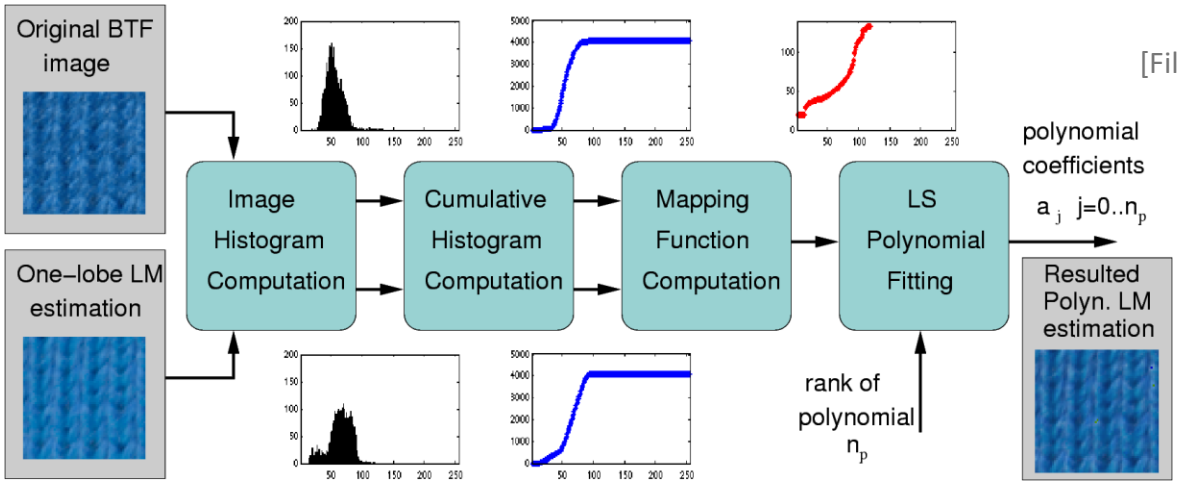
$$\mathcal{R}_v(r_1, r_2, i, v) \approx \rho_{d,r_1,r_2} + \rho_{s,r_1,r_2,k} \sum_k^{n_l} [\omega_i^T \mathbf{D}_{r_1,r_2,k}]^{n_{r_1,r_2,k}}$$

[Filip & Haindl 04] – polynomial extension of Lafortune model

☑ good visual quality

☒ lower compression $\approx \frac{1}{20}$

$$\mathcal{R}_v(r_1, r_2, i, v) \approx \sum_{j=0}^{n_p} a_{r_3,v,i,j} [\rho_v(r)(\omega_i^T \mathbf{D}_v(r))^{n_v(r)}]^j$$



[Filip & Haindl 04]

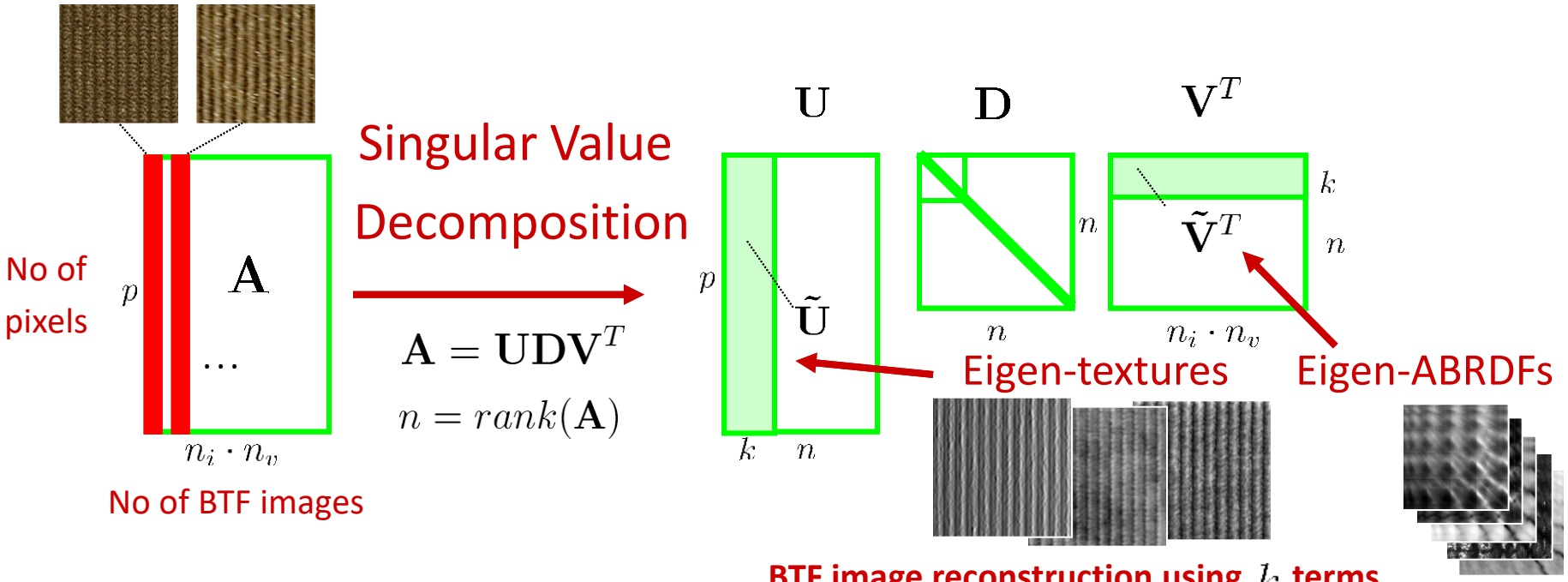
PCA vs. SVD – Dimensionality Reduction and Data Compression

- **SVD (Singular Value Decomposition)**: Factorizes any matrix into orthogonal bases and singular values.
- **PCA (Principal Component Analysis)**: Finds orthogonal directions of maximum data variance.
- **Key relationship:** PCA is equivalent to applying SVD to mean-centered data.
- **Compression:** Both retain the k most significant components to obtain a low-rank approximation.

Property	SVD	PCA
Main purpose	Matrix factorization	Variance analysis
Input	Original data matrix	Mean-centered data
Basis	Singular vectors	Principal components
Component importance	Singular values σ_i	Explained variance λ_i
Optimization	Minimum rank-k reconstruction error	Maximum retained variance

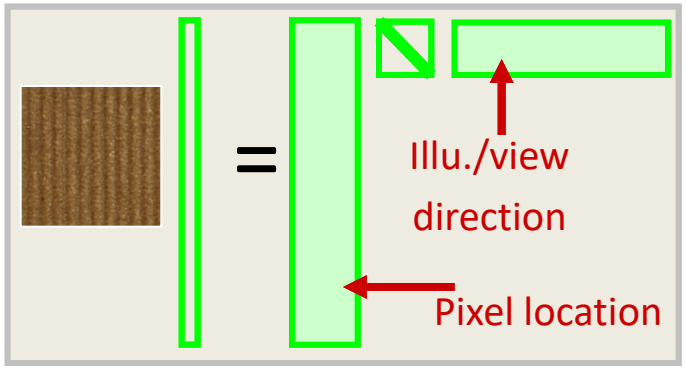
SVD-Based BTF Factorization

General algebraic matrix factorization



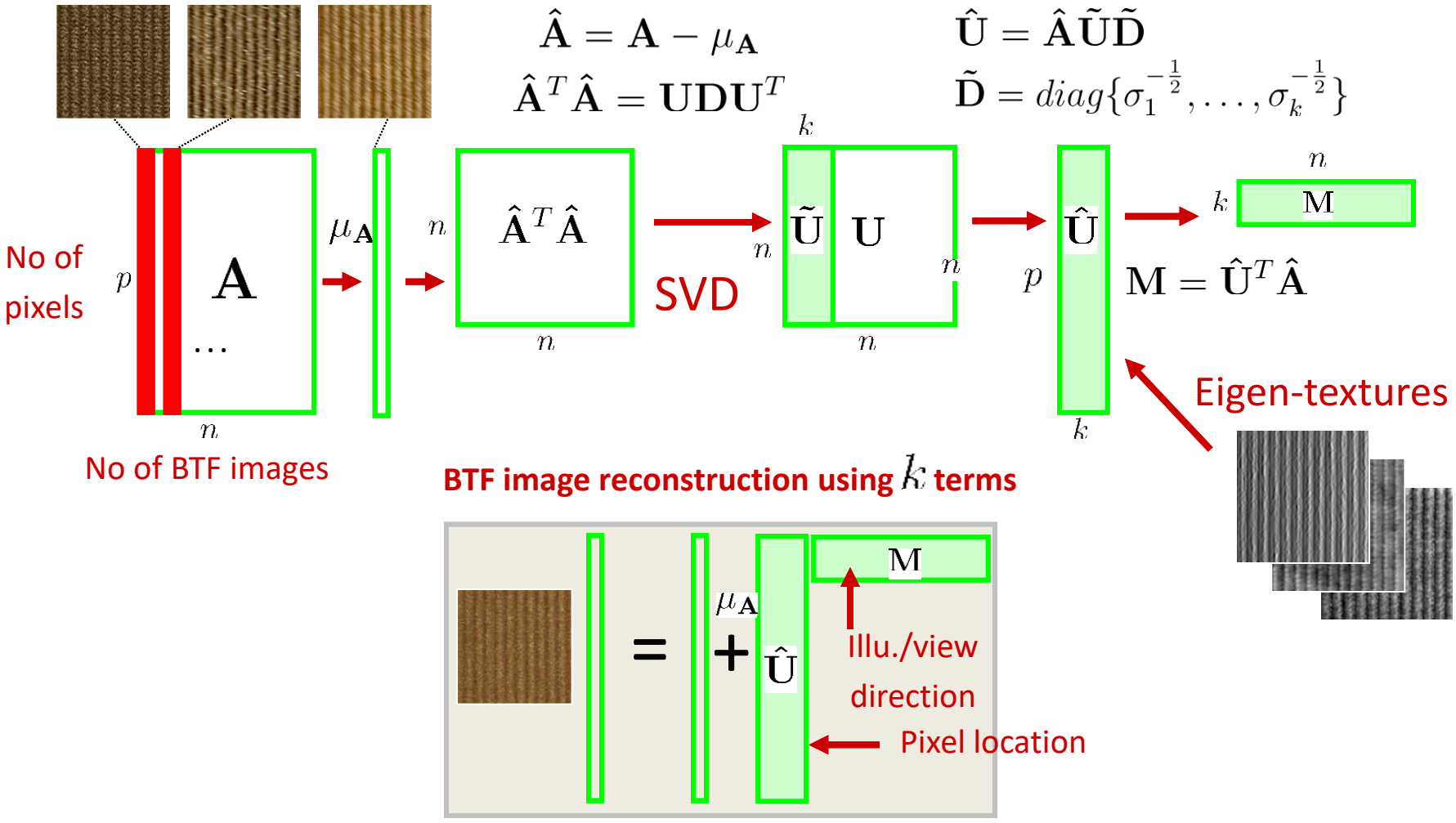
BTF image reconstruction using k terms

$$BTF(r_1, r_2, i, v) \approx \sum_{j=1}^{k} u_j(r_1, r_2)\sigma_j v_j(i, v)$$



PCA-Based BTF Factorization

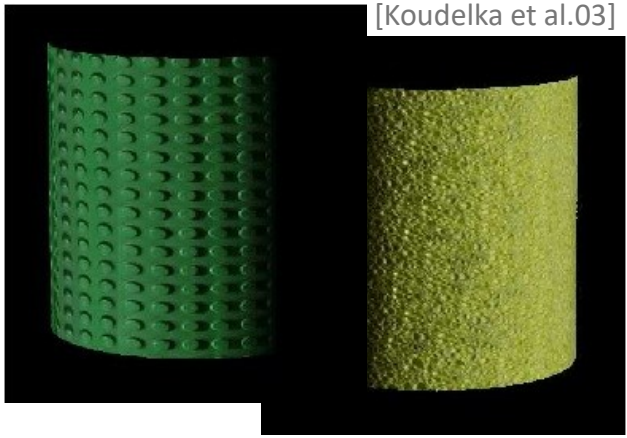
Statistical method for identification of the highest variability directions in data



Full BTF Factorization

[Koudelka et al. 03] – PCA of all BTF images in texture space.

$$BTF(r_1, r_2, i, v) \approx \sum_{k=1}^{n_c} \mathbf{u}_k(i, v)\sigma_k \mathbf{v}_k(r_1, r_2)$$



[Koudelka et al.03]

☑ high compression $\approx \frac{1}{1000}$, quality control

☒ long reconstruction times, lower quality

[Guthe et al. 09] – PCA of all BTF images in ABRDF space.

- Additional transformation $\boldsymbol{T}$ to minimize visual difference
- Visual difference ⇨ spatio-temporal filtering ⇨ HVS cone responses, contrast sensitivity function

$$BTF(r_1, r_2, i, v) \approx \sum_{k=1}^{n_c} T[\mathbf{u}_k(r_1, r_2)]\sigma_k T[\mathbf{v}_k(i, v)]$$

[Guthe et al.09]



☑ high compression $\approx \frac{1}{500}$, perceptual quality measure

☒ long compression times

Per-View BTF Factorization

[Sattler et al. 03] – PCA of all BTF images in individual view directions.

$$\mathcal{R}_v(r_1, r_2, i) \approx \sum_{k=1}^{n_c} \mathbf{u}_{v,k}(i)\sigma_k \mathbf{v}_{v,k}(r_1, r_2)$$

☑ fast compression & reconstruction, good visual quality

☒ low compression rates $\approx \frac{1}{20}$

[Sattler et al.03]



[Wong & Leung 03] – compress illumination dependent data ⇨ ***spherical harmonics***. The coefficient planes further coded using a discrete wavelet transformation.

☑ reasonable compression, controllable by a number of components

☒ lower reconstruction speed – requires inverse DWT

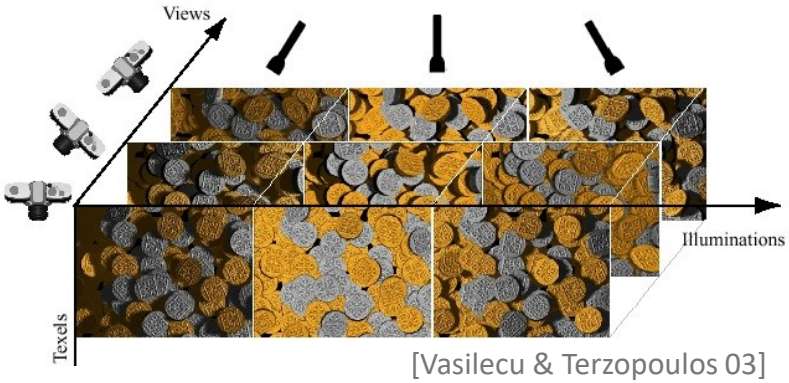
Full BTF Factorization

[Vasilescu & Terzopoulos 03] – BTF images as vectors in 3D tensor ⇨ multi-modal SVD ⇨ controllable compression of view/illum. effects.

$$\mathcal{B} = \mathcal{Z} \times_1 \mathbf{U}_{tex} \times_2 \mathbf{U}_i \times_3 \mathbf{U}_v$$

$$\mathcal{T} = \mathcal{B} \times_2 \mathbf{U}_i \times_3 \mathbf{U}_v$$

$$BTF(i,v) = \mathcal{T} \times_2 \mathbf{i}^T \times_3 \mathbf{v}^T$$



[Vasilecu & Terzopoulos 03]

[Wang et al. 04] – Instead of 3D texel-illumination-view tensor, BTF data directly in 4D tensor ⇨ preserving spatial relationships in individual BTF images.

☑ compact representation, controllable compression $\approx \frac{1}{100}$

☒ many components interpolation slows-down rendering

Full BTF Factorization

[Ruiters & Klein 09] – **sparse tensor decomposition** (K-SVD) into small dictionary tensor and two sparse tensors.

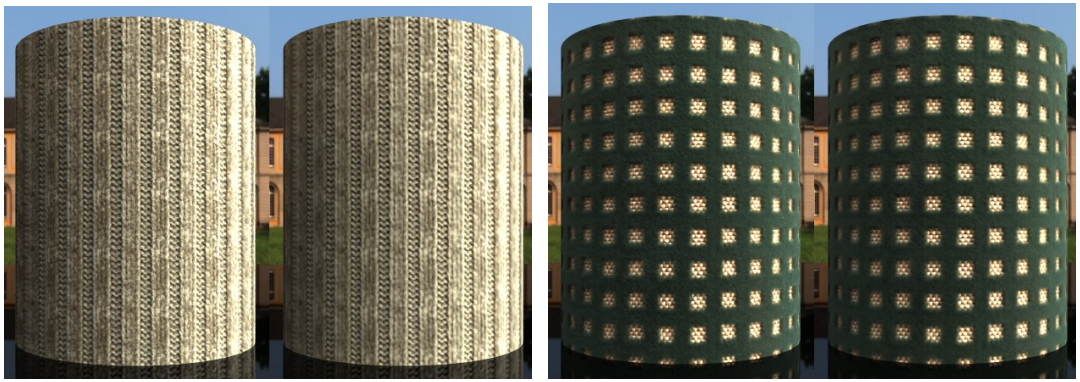
$$BTF(\lambda, r, i, v) \approx \mathcal{L}_{\lambda ij} \times \mathcal{V}_{jvk} \times \mathcal{P}_{kr}$$

$$\mathcal{L}_{\lambda ij} \in \mathbb{R}^{colors \times lights \times D_1}, \quad \mathcal{V}_{jvk} \in \mathbb{R}^{D_1 \times views \times D_2}, \quad \mathbf{P}_{kr} \in \mathbb{R}^{D_2 \times pixels}$$

☑ compact ⇨ high compression $\approx \frac{1}{1000}$

☒ slow compression, long rendering times for high visual quality, no hardware implementation

[Ruiters & Klein 09]



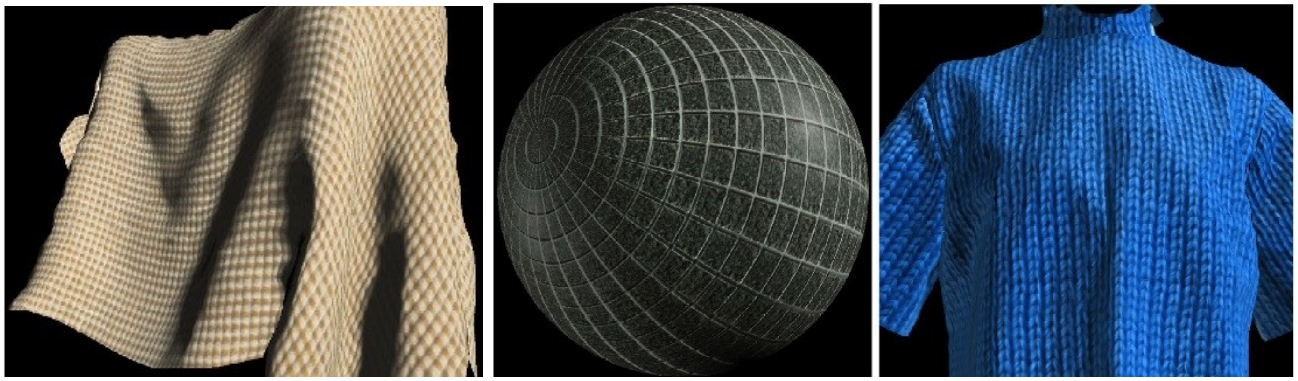
Per-Cluster Factorization

[Muller et al. 03] – combination of iterative clustering of ABRDF data (modified K-Means) & PCA in each cluster. Eigen-image reconstruction error ⇨ distance measure in the clustering process.

$$BTF(r_1, r_2, i, v) \approx \sum_{k=1}^{n_c} \mathbf{u}_{m(r_1,r_2),k}(x, y)\sigma_{m(r_1,r_2),k}\mathbf{v}_{m(r_1,r_2),k}(i, v)$$

☑ high compression $\approx \frac{1}{300}$, good quality

☒ long iterative clustering & compression times, mip-mapping



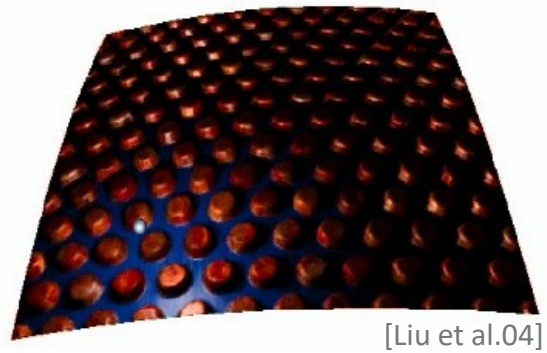
[Muller et al.03]

BTF Space Clustering + Factorisation

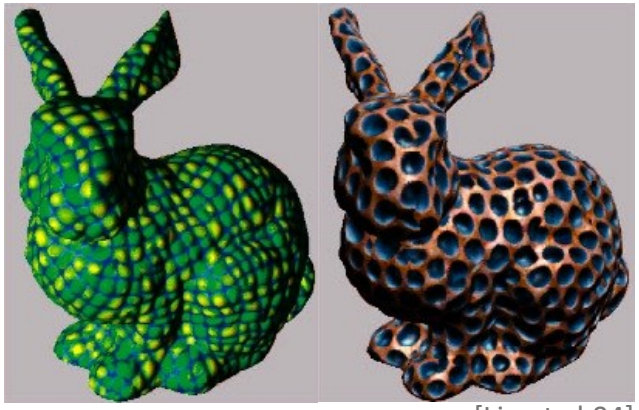
[Leung & Malik 01] – 3D textons ⇨ vocabulary of prototype tiny surface patches with associated local geometric and photometric properties. Appearance vectors ⇨ set of linear Gaussian derivative filter outputs.

[Liu et al. 04] – BTF sample ⇨ small number of 4D point apperance functions (textons) multiplied by 2D geometry maps. Textons compressed by linear factorization (SVD).

☑ texton based synthesis, fast HW implemented, high compression



[Liu et al.04]



[Liu et al.04]

BTF Space Clustering + BRDF Model

[Filip & Haindl 05] – ABRDFs clustering (K-means) + polynomial expansion of Lafortune model in cluster centers.

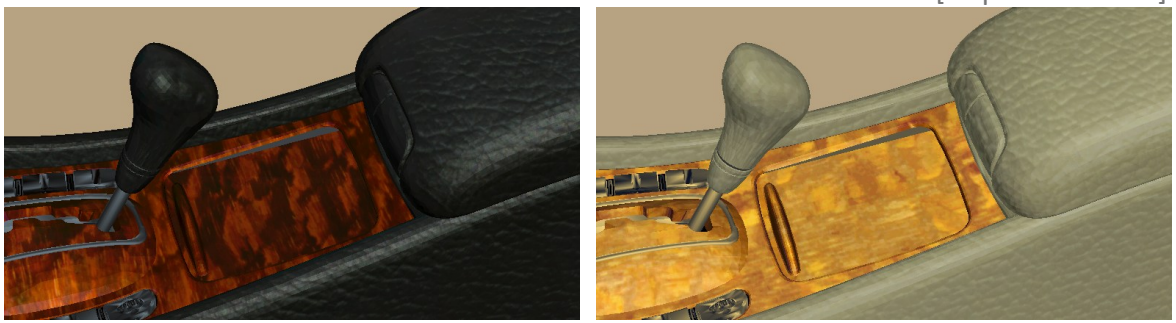
$$
\begin{aligned}
\rho(r_1,r_2)_v &= K_{v,1}(I_v(r_1,r_2)) \\
D(r_1,r_2)_{v,X} &= K_{v,2}(I_v(r_1,r_2)) \\
D(r_1,r_2)_{v,Y} &= K_{v,3}(I_v(r_1,r_2)) \\
D(r_1,r_2)_{v,Z} &= K_{v,4}(I_v(r_1,r_2)) \\
n(r_1,r_2)_v &= K_{v,5}(I_v(r_1,r_2))
\end{aligned}
$$

$$
\mathcal{R}_v(r_1,r_2,i,v) \approx \sum_{j=0}^{n_p} a_{r_3,v,i,j}\left[\rho_v(r)(\omega_i^T \mathbf{D}_v(r))^{n_v(r)}\right]^j
$$

☑ compression $\approx \frac{1}{200}$, fast fitting of several ABRDFs only

☒ quantization artifacts

[Filip & Haindl 05]

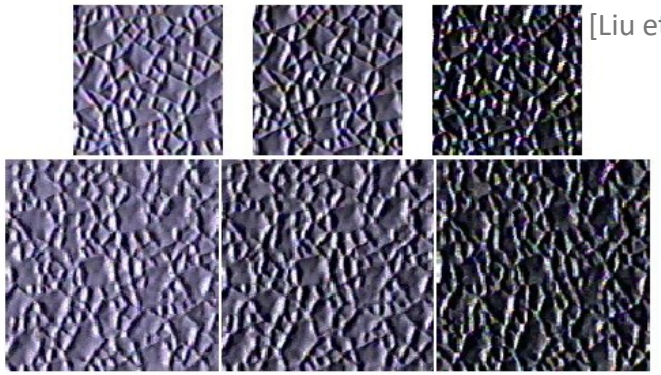


Combining Geometry and Reflectance

[Liu et al. 01] – spare set of small BTF image tiles combined according to range-map to produce novel BTF image of arbitrary size.

☑ arbitrary size BTF synthesis

☒ very slow, low BTF compression



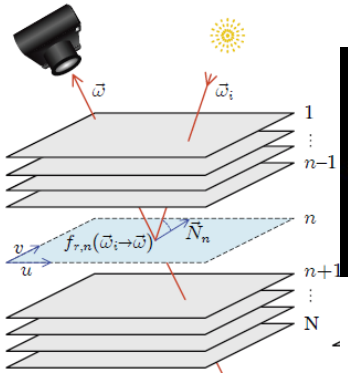
[Liu et al. 01]

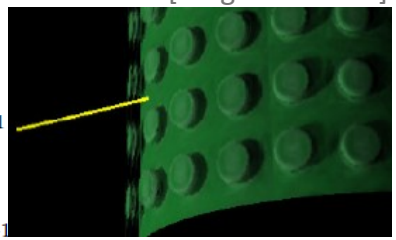
[Magda & Kriegman 06] – separate *geometric information* ⇨ layered volumetric model of material structure, and *reflectance data* ⇨ Lafortune BRDF model.

☑ high compression, easy BTF interpolation

☒ Number of layers and height of the sample

⇨ set explicitly, high grazing angles artifacts





[Magda et al. 06]

Combining Geometry and Reflectance

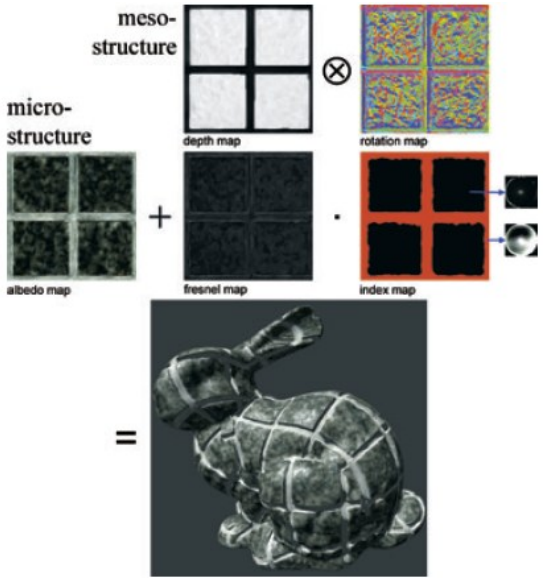
[Menzel & Guthe 09] – **geometric BRDFs** = BTF separation to intuitive and online editable texture maps:

- meso & micro scale geometry ⇨ depth & tangent 2D maps
- light interactions ⇨ Ashikhmin [2006] analytic BRDF model
- segmentation to basis materials

☑ reasonable visual quality, high compression $\approx \frac{1}{1000}$, interactive editing without need of compression

☒ for opaque samples; no sub-surface scattering inter-reffection effects; shadows reconstructed from depth map; BRDF model ⇨ chromatic errors

[Menzel & Guthe 09]



Multilevel Vector Quantization

[Havran et al. 10] – BTF multi-level vector quantization algorithm

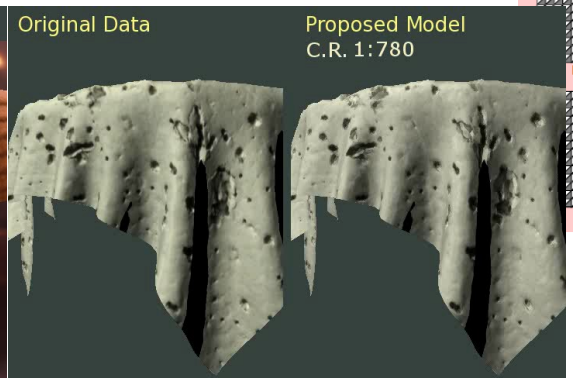
- BTF parameterized ⇨ set of 1D, 2D, 3D, and 4D data slices
- Multi-level code-books of slices (indices/scales).
- reconstruction ⇨ fast chained indexing in nested code-books

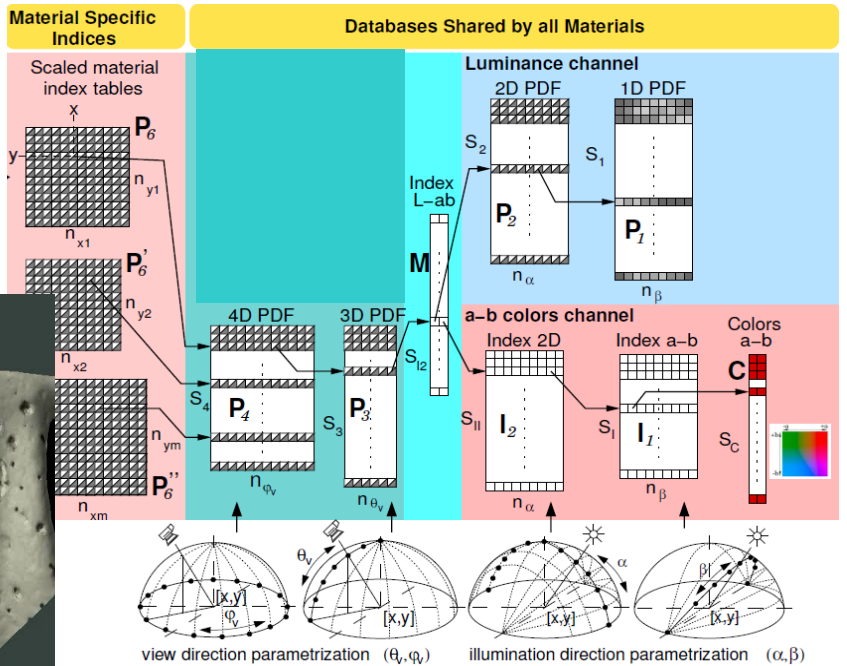
☑ high compression $\approx \frac{1}{700}$, direct importance sampling support, hardware implementation

☒ time demanding generation of optimized codebooks

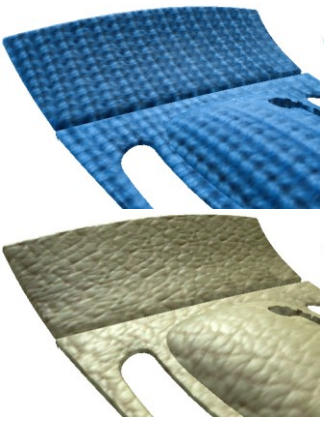
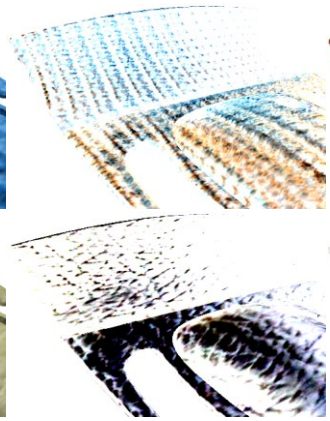
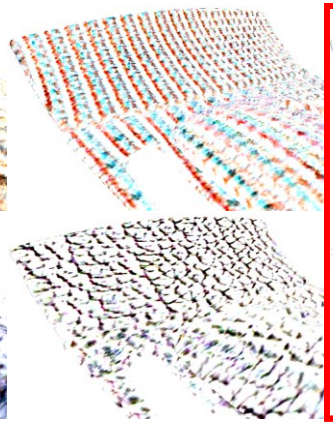
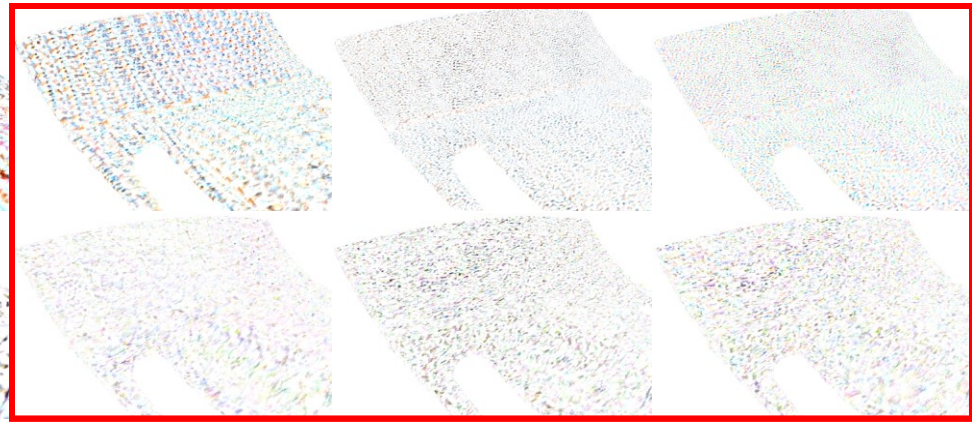
[Havran et al. 10]







Selected Methods Comparison

	Per-view polynomials [Malzbender 01]	**Per-view Lafortune** [FilipHaindl 04]	**Per-view PCA** [Sattler 03]	**Entire PCA** [Koudelka 03]	**Per-cluster PCA** [Muller 03]
					
	10 times difference		Parameters psychophysically estimated		
Compression (average)	$\approx \frac{1}{14}$	$\approx \frac{1}{16}$	$\approx \frac{1}{7}$	$\approx \frac{1}{91}$	$\approx \frac{1}{31}$
Analysis time	≈ 165	≈ 136	≈ 10	≈ 3862	≈ 1098
Synthesis time (25x25 pix.) [s]	≈ 1	≈ 1	≈ 2	≈ 8	≈ 22

Survey **[Filip & Haindl 09]**

Conclusions on BTF Compression



- BTF ⇨ massive data ⇨ lot of redundancy
- Compression methods
  - **Remove** data **redundancy**
  - Preserve **perceptually important** visual features
  - Allow **random access** for **fast** data reconstruction
- Compression ⇨ reduction of measured data
- Synthesis ⇨ arbitrary BTF sample enlargement
- Synthesis (usually with compression) = **Modelling**
- **BTF data modelling** ⇨ required in practical applications

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