# TensorTextures: <br> Multilinear Image-Based Rendering 

Computer Graphics

## Motivation

- Goal: Generation of photorealistic virtual environments
- Classical Computer Graphics: Model - based

Rendering

- From object models to images
- Model specifies geometry of a scene and surface properties
- Images are generated by projecting 3D model onto an image plane and computing surface shading
- Photorealism requires complex models
- Difficult
- Time consuming


## Image-Based Rendering

[Gortler et al. 1996, Levoy \& Hanrahan 1996, Debevec, Taylor \& Malik 1996, ...]

- World is modeled by a collection of images (and possibly some coarse geometry)
- These images are used to synthesize novel images representing the scene from arbitrary viewpoints and illuminations
- Advantages:
- Rendering is decoupled from the scene complexity
- Photorealism is improved


## Our Contribution

- We introduce a tensor framework for image-based rendering (IBR)
- Specifically, rendering of 3D textured surfaces
- Surface appearance is determined by the complex interaction of multiple factors:
- Scene geometry
- Illumination
- Imaging


## Bidirectional Texture Function

- BTF: Captures the appearance of extended textured surfaces with
- Spatially varying reflectance
- Surface mesostructure (3D texture)
- Subsurface scattering
- Etc.
- Generalization of BRDF, which accounts only for surface microstructure at a point


BTF Texture Mapping
[Dana et al. 1999]

|  | Concrete | Pebbles | Plaster |
| :---: | :---: | :---: | :---: |
| Standard <br> Texture Mapping |  |  | $35$ |
| BTF <br> Texture Mapping | $8$ |  |  |

## BTF

- Reflectance as a function of position on surface, view direction, and illumination direction

$$
\begin{aligned}
& f_{B T F}\left(x, y, \theta_{v}, \phi_{v}, \theta_{i}, \phi_{i}\right) \\
& \begin{array}{lll}
\begin{array}{l}
\text { position } \\
\text { on surface }
\end{array} & \begin{array}{l}
\text { view } \\
\text { direction }
\end{array} & \begin{array}{l}
\text { illumination } \\
\text { direction }
\end{array}
\end{array} \\
& \text { on surface } \underbrace{\text { direction }}_{\text {photometric angles }}
\end{aligned}
$$

- The BTF captures shading and mesostructural self-shadowing, self-occlusion, interreflection

TensorTexture Mapping


TensorTextures: Learns BTFs from ensembles of sample images Nonlinear generative BTF model

## TensorTextures Overview

1. Mathematical foundations: Eigentextures

- Linear Analysis / Principal Components Analysis
- fixed viewpoint, changing illumination
- changing viewpoint and illumination

2. TensorTextures

- Nonlinear (multilinear) Analysis / Tensor decomposition

3. Experiments and results

THE FOLLOWING PREVIEW has been approved for

## ALL AUDIENCES

BY THE MOTION PICTURE DISASSOCIATION OF AMERICA


## "Eigentextures" - PCA (Matrix Algebra)

Simple Data Acquisition:
Fixed Viewpoint, Varying Illumination


Sample images are points in "pixel space"


Principal Components Analysis (PCA) Eigentextures


Eigentextures - captures variation across illuminations

The 1-Mode Case
(fixed viewpoint, varying illumination)


Eigentextures - captures variation across illuminations


Image Representation using PCA
$\mathbf{d}=\mathbf{U c}$


Its PCA Representation
$c_{0}+c_{1}+c_{2}+\cdots+c_{k}$

- Note: This is a linear representation

Sampling Multiple Viewpoints and Illuminations


- This poses a 3-mode BTF estimation problem - Viewpoint, illumination, and pixel modes

Rectifying Homography

- Image unwarping $\mathbf{p}^{\prime}=\mathbf{H p}$
- H can be computed given at least 4 fiducials $\mathbf{p}^{\prime}$ \& $\mathbf{p}$ 줄



## PCA Reconstruction



111 basis vectors


33 basis vectors


## TensorTextures <br> (Tensor Algebra)

TensorTexture: 3-Mode Data Tensor


## Background on Tensor Decomposition

- Factor Analysis:

Psychometrics, Econometrics, Chemometrics,

- SVD:
- [Beltrani, 1873] (Giornalle di Matematiche 11) "Sulle funzioni bilineari"
- [Eckart and Young, 1936] (Psychometrika)
"The approximation of one matrix by another of lower rank"
- 3-Way Factor Analysis:
- [Tucker,1966] (Psychometrika)
"Some mathematical notes on three mode factor analysis"
- [Kroonenberg and De Leeuw, 1980] - 3-mode ALS
- N-Way Factor Analysis:
- [Kapteyn, Neudecker, and Wansbeek, 1986] - N-way ALS factor analysis
- [Franc, 1992] - tensor algebra
- [Denis \& Dhorne, 1989]
[de Lathauwer, 1997$]$


## Matrix Decomposition - SVD



- A matrix $\mathbf{D} \in I R^{4^{x / 2}}$ has a column and row space
- SVD orthogonalizes these spaces and decomposes D

$$
\mathbf{D}=\mathbf{U}_{1} \mathbf{S} \underbrace{T}_{2} \quad\left(\mathbf{U}_{1} \text { contains the "eigentextures" }\right)
$$

- Rewrite in terms of mode-n products

$$
\mathbf{D}=\mathbf{S} \quad x_{1} U_{1} x_{2} U_{2}
$$

## Tensor Decomposition

- $\mathcal{D}$ is a n -dimensional matrix, comprising N -spaces
- N-mode SVD is the natural generalization of SVD

$$
\mathbf{D}=\mathbf{U}_{1} \mathbf{S U}_{2}^{T} \quad \longrightarrow \quad \mathbf{D}=\mathbf{S} \times_{1} \mathbf{U}_{1} \times_{2} \mathbf{U}_{2}
$$

- N-mode SVD orthogonalizes these spaces \& decomposes
$\mathcal{D}$ as the mode-n product of N -orthogonal spaces

$$
D=Z x_{1} U_{1} \times_{2} U_{2} x_{3} U_{3} \times_{4} \not \cdots x_{N} U_{N}
$$

- $Z$ core tensor; governs interaction between mode matrices
- $\mathbf{U}_{n}$ mode-n matrix, is the column space of $\mathbf{D}_{(n)}$


## Tensor Decomposition


$\mathcal{D}=\mathcal{Z}_{x_{1}} \mathbf{U}_{\text {texels }} \times_{2} \mathbf{U}_{\text {illums. }} x_{3} \mathbf{U}_{\text {views }}$ $=\sum_{r_{1}=1}^{R_{1}} \sum_{r_{2}=1}^{R_{2}} \sum_{r_{3}=1}^{R_{3}} \sigma_{r_{1}, r_{2}} \mathbf{u}_{\text {exeels }, r_{1}} \circ \mathbf{u}_{\text {Ilums }, r_{2}} \circ \mathbf{u}_{\text {views }, r_{3}}$
$\operatorname{vec}(\mathcal{D})=\left(\mathbf{U}_{\text {views }} \otimes \mathbf{U}_{\text {illums }} \otimes \mathbf{U}_{\text {texels }}\right) \operatorname{vec}(Z)$

## TensorTexture Decomposition



$$
\mathscr{D}=\mathcal{Z} x_{1} \mathbf{U}_{\text {texels }} \times_{2} \mathbf{U}_{\text {illums }} \times_{3} \mathbf{U}_{\text {views }}
$$

## N-Mode SVD Algorithm

1. For $\mathrm{n}=1, \ldots, \mathrm{~N}$, compute matrix $\mathbf{U}_{n}$ by
computing the SVD of the flattened matrix $\mathbf{D}$ and setting $\mathbf{U}_{n}$ to be the left matrix of the SVD.
2. Solve for the core tensor as follows

$$
\boldsymbol{Z}=\boldsymbol{D} \quad \mathbf{x}_{1} \mathbf{U}_{1}^{T} \mathbf{x}_{2} \mathbf{U}_{2}^{T} \cdots \mathbf{x}_{N} \mathbf{U}_{N}^{T}
$$

## Computing $U_{\text {views }}$

- $\mathrm{D}_{\text {(views }}$ filfiews $\mathbb{T}$ along the view point dimension



Texels


Computing $\mathrm{U}_{\text {illums }}$
Views

- $\mathrm{D}_{\text {(illunesilaiten }} \mathrm{J}$ alona the a illuminatu, dimension


Texels


## Mode-N Product

- Mode-n product is a generalization of the product of two matrices
- It is the product of a tensor with a matrix
- Mode-n product of $\quad$ and $\mathbf{M}=I R^{J_{n} x I_{n}}$ $\mathcal{B} \in I R^{I_{1} \mathrm{x} \ldots I_{n-1} \mathrm{x} . J_{n} \times I_{n+1} \times \mathrm{x} \times x I_{N}} \quad \mathcal{A} \in I R^{I_{1} \times \ldots x I_{n} \times \ldots x I_{N}}$


TensorTextures: $\mathcal{T}=\mathcal{Z}_{x_{3}} \mathrm{U}_{\text {pixels }}$


TensorTextures:
explicitly represent
covariance across
factors


## N-Mode SVD Algorithm

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2. Solve for the core tensor as follows

$$
Z=D \mathbf{X}_{1} \mathbf{U}_{1}^{T} \mathbf{X}_{2} \mathbf{U}_{2}^{T} \cdots \mathbf{X}_{N} \mathbf{U}_{N}^{T}
$$

## Mode-N Product

$N$-th order tensor $\mathcal{A} \in \Re^{I_{1} \times I_{2} \times \cdots I_{N}}$
matrix (2-nd order tensor)

$$
\mathbf{M} \in \mathfrak{R}^{J_{n} \times I_{n}}
$$

mode- $n$ product:

$$
\mathcal{B}=\mathcal{A} \times_{n} \mathbf{M} \quad \text { where } \quad \mathbf{B}_{(n)}=\mathbf{M} \mathbf{A}_{(n)}
$$

TensorTextures: $\mathcal{T}=\mathcal{Z}_{x_{3}} \mathrm{U}_{\text {pixels }}$


## TensorTextures:

explicitly represent
covariance across
factors


## TensorTextures vs. PCA

- Multilinear Analysis / TensorTextures:

$$
\mathcal{D}=Z \mathrm{x}_{1} \mathbf{U}_{\text {texels }} \mathrm{x}_{2} \mathbf{U}_{\text {illums. }} \mathrm{x}_{3} \mathbf{U}_{\text {views }}
$$

- Linear Analysis :
$\underbrace{\mathbf{D}_{\text {(everes) }}}=\underbrace{\mathbf{U}_{\text {texels }}} \underbrace{\mathbf{Z}_{\text {(texes) }}\left(\mathbf{U}_{\text {vews }} \otimes \mathbf{U}_{\text {ilums }}\right)^{\top}}$ data matrix basis matrix coefficient matrix
- TensorTextures subsumes PCA / Eigentextures


## Strategic Dimensionality Reduction

TensorTextures
Dimensionality Reduction

## System Diagram



Strategic Dimensionality Reduction



Computing $\mathbf{v}_{\text {new }}$ : Homogeneous Barycentric Blend

$\mathbf{v}_{\text {now }}=\mathbf{v}_{i} \Delta t_{i}+\mathbf{v}_{j} \Delta t_{j}+\mathbf{v}_{k} \Delta t_{k}$
$\Delta t_{i}+\Delta t_{j}+\Delta t_{k}=1$
$\Delta t_{i}=\frac{\left(\left(\mathbf{V}_{j}-\mathbf{V}_{\text {new }}\right) \times\left(\mathbf{V}_{k}-\mathbf{V}_{\text {new }}\right)\right)}{\left(\left(\mathbf{V}_{j}-\mathbf{V}_{i}\right) \times\left(\mathbf{V}_{k}-\mathbf{V}_{i}\right)\right)}$

Synthesis Algorithm / Texture Representation

$$
\mathbf{d}=\int \times_{2} \mathbf{l}_{n e w}^{T} \times_{3} \mathbf{v}_{n e w}^{T}
$$



Rendered Textures for Cylinder


Rendered Texture for a Planar Surface


## Rendering on Arbitrary Geometry

Bonn natural BTF datasets TensorTextures renderings


