Making choices in multi-dimensional parameter spaces

PhD thesis defence

Steven Bergner

gruvi 🔲 graphics + usability + visualization

Model adjustment at different levels

- User-driven experimentation: Use cases for paraglide
- Criteria optimization: Lighting design
- Theoretical analysis: Sampling in volume rendering
- Discretizing a region: Lattices with rotational dilation
- Summary and conclusion



Data acquisition and visualization

Turning code into data

- Computer simulation code
- Function abstraction
 - Variables: input, output, and algorithm specific
 - Deterministic code



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More cases

- Parameter space segmentation
- Bio-medical imaging algorithm
- Fuel cell design
- Scene lighting configuration
- Raycasting step size parameter





User Interaction

Computation

Set up compute node







• Setup compute node





- Setup compute node
- Choose variables



- Setup compute node
- Choose variables
- Choose region





- Setup compute node
- Choose variables
- Choose region
- Sample and compute





- Setup compute node
- Choose variables
- Choose region
- Sample and compute
- Compute features





- Setup compute node
- Choose variables
- Choose region
- Sample and compute
- Compute features
- View, predict, diagnose







- Tensor product of value levels for each dimension
 - Nested for-loops
 - Cost is exponential in #dims



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stack:current	2 1 0 85 <u>110 135 160</u> 185
stack:hdLength	10 5 0 0.1
stack:manifoldType	10 5 0 1
stack:meaWidth	10 5 0
stack:numCells	10 5 0 10
stack:numChannels	10 5 0 36
stack:tempIn	3 2 1 0 334 336 38 340 342



Paraglide summary

- Longitudinal study showed use of parameter space partitioning
- Requirements informed follow-up projects
- Alternative user interaction
 - Dimensionally reduced slider embedding
 - Mixing board
- Video demo



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Roadmap

- From light to colour
- Efficient light model
- Designing spectra for lights and materials
- Evaluation
- Applications















Light 2

- Metamers
- Different Spectra give same
 RGB

 Light 2

 Image: Constrained state stat

- Metamers
 - Different Spectra give same RGB
- Constant Colours
 - Metamers under changing light

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- Spectra give RGB triple = 0

Light 2

- Metamers
 - Different Spectra give same RGB
- Constant Colours
 - Metamers under changing light
- Metameric Blacks
 - Spectra give RGB triple = 0
- Effective choice of light & material palette needed!

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Colour

- Fit the desired colour or metamer
- Smoothness
 - Regularize solution and reduce extrema
- Minimal error in linear model
 - Minimal colour difference when illumination bounce is computed in linear subspace
- Positivity
 - Produce physically plausible spectra

• Instead of equation system $\mathbf{M}\vec{x} = \vec{y}$ for spectrum \vec{x} Solve normal equation $\operatorname{argmin}_{\vec{x}} \|\mathbf{M}\vec{x} - \vec{y}\|$

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Instead of equation system $\mathbf{M}\vec{x} = \vec{y} \quad \text{for spectrum } \vec{x}$ Solve normal equation $\operatorname{argmin}_{\vec{x}} \|\mathbf{M}\vec{x} - \vec{y}\|$

- Colour: $\operatorname{argmin}_{\vec{x}} \left\| \begin{bmatrix} \mathbf{m}_{red} \\ \mathbf{m}_{green} \\ \mathbf{m}_{blue} \end{bmatrix} \operatorname{diag}(\vec{S})\vec{x} - \begin{bmatrix} c_r \\ c_g \\ c_b \end{bmatrix} \right\|$ - Smoothness: $\operatorname{argmin}_{\vec{x}} \left\| \begin{bmatrix} -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ 0 & 0 & \cdots & -1 & 2 & -1 \end{bmatrix} \vec{x} - \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \right\|$

Instead of equation system $\mathbf{M}\vec{x} = \vec{y} \quad \text{for spectrum } \vec{x}$ Solve normal equation $\operatorname{argmin}_{\vec{x}} \|\mathbf{M}\vec{x} - \vec{y}\|$

 $-\operatorname{Colour:} \operatorname{argmin}_{\vec{x}} \left\| \begin{bmatrix} \mathbf{m}_{red} \\ \mathbf{m}_{green} \\ \mathbf{m}_{blue} \end{bmatrix} \operatorname{diag}(\vec{S})\vec{x} - \begin{bmatrix} c_r \\ c_g \\ c_b \end{bmatrix} \right\|$ $-\operatorname{Smoothness:} \operatorname{argmin}_{\vec{x}} \left\| \begin{bmatrix} -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ & & \ddots & & \\ 0 & 0 & \cdots & -1 & 2 & -1 \end{bmatrix} \vec{x} - \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \right\|$

- Weight the criteria and combine as stacked matrix
 - Global minimum error solution via pseudo-inverse of ${f M}$
 - Positivity through quadratic programming

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Given: Output	Goal: Input











Image based re-lighting



Image based re-lighting



Image based re-lighting



Applications in Graphics and Visualization



 Additional texture details appear under changing illumination

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 Map data value f to optical properties using a transfer function g(f(x))

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- Then shading+compositing



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Intuition Analysis

Application



Intuition Analysis Application





Intuition Analysis Appli

Application







Intuition Analysis Application

Example of g(f(x))

0.5

-3

-2

 $^{-1}$

1

0

g(f(x)) sampled by $\frac{\pi}{2} v_f v_g$

2

3







Intuition Analysis Application





Intuition

Application

Composition in Frequency Domain $g(y) = \frac{1}{\sqrt{2\pi}} \int_{R} G(l) e^{il \cdot y} dl$



Application

Composition in Frequency Domain $h(x) = g(f(x)) = \frac{1}{\sqrt{2\pi}} \int_{R} G(l) e^{il \cdot f(x)} dl$



Intuition

Application

Composition in Frequency Domain $h(x) = g(f(x)) = \frac{1}{\sqrt{2\pi}} \int_{R} G(l) e^{il \cdot f(x)} dl$

H(k)

 $\int_{B} G(l) e^{il \cdot f(x)} dl$


Application

Composition in Frequency Domain $h(x) = g(f(x)) = \frac{1}{\sqrt{2\pi}} \int_{R} G(l) e^{il \cdot f(x)} dl$

Analysis

 $H(k) = \frac{1}{2\pi} \iint_{B} \iint_{B} G(l) e^{il \cdot f(x)} dl e^{-ik \cdot x} dx$



Intuition Analysis

Application

Composition in Frequency Domain $h(x) = g(f(x)) = \frac{1}{\sqrt{2\pi}} \int_{R} G(l) e^{il \cdot f(x)} dl$

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$$H(k) = \frac{1}{2\pi} \int_R G(l) \int_R e^{il \cdot f(x)} e^{-ik \cdot x} dx dl$$



Intuition Analysis

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$$P(k,l) = \int_R e^{i(l \cdot f(x) - k \cdot x)} dx$$



 $Visualizing P(k,l) = \int_{R} e^{i(l \cdot f(x) - k \cdot x)} dx \quad H(k) = \frac{1}{2\pi} \langle G(\cdot), P(k, \cdot) \rangle$



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Analysis

Application





Analysis

Application





Analysis

Application





Analysis

Application

Visualizing P(k,l)
Slopes of lines in P(k,l) are related to 1/f'(x)





Intuition Analysis Application

- Slopes of lines in P(k,l) are related to 1/f'(x)
- Extremal slopes bounding the wedge are 1/max(f')





Analysis

Application

Method of stationary phase $P(k,l) = \int_{R} e^{i(l \cdot f(x) - k \cdot x)} dx$





Analysis

Application

Method of stationary phase $P(k,l) = \int_{R} e^{i(l \cdot f(x) - k \cdot x)} dx$





Analysis

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Method of stationary phase $P(k,l) = \int_{R} e^{i(l \cdot f(x) - k \cdot x)} dx$





Application

Method of stationary phase $P(k,l) = \int_{R} e^{i(l \cdot f(x) - k \cdot x)} dx$

- Taylor expansion around points of stationary phase
- Exponential drop-off at maximum $l \cdot \max |f'| = k$





Analysis

Application

Method of stationary phase $P(k,l) = \int_{R} e^{i(l \cdot f(x) - k \cdot x)} dx$

- Taylor expansion around points of stationary phase
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Analysis

Application

Adaptive Raycasting

Same number of samples





Intuition Analysis Application Adaptive Raycasting SNR Quality vs. Performance

Ground-truth: Computed at a fixed sampling distance of 0.06125





Summary

- Proper sampling of combined signal g(f(x)): $v_h = \max(||f'||) \cdot v_g$
- Solved a fundamental problem of rendering
- Composition is a general data processing operation



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Point lattices

• Definition via basis R





Point lattices

• Definition via basis $\{\mathbf{R}k : k \in \mathbb{Z}^n\}$



4



$$\mathbf{R} = \left[\begin{array}{cc} 1 & 0 \\ 0 & 1 \end{array} \right]$$





$$\mathbf{R} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \mathbf{K} = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} = 2\mathbf{I} \quad \det \mathbf{K} = 2^n = 4$$





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Reduction factor is exponential in n



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$$\mathbf{R} = \left[\begin{array}{cc} 1 & 0 \\ 0 & 1 \end{array} \right]$$





$$\mathbf{R} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \mathbf{K} = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$$











This low rate dilation does not exist for integer lattices with n > 2[Van De Ville, Blu, Unser, SPL 05]





This low rate dilation does not exist for integer lattices with n > 2[Van De Ville, Blu, Unser, SPL 05]

However, possible for irrational R !



$$\mathbf{R} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \mathbf{K} = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$$









Construction

 $\mathbf{QR} = \mathbf{RK}$ with $\mathbf{Q}^T \mathbf{Q} = \alpha^2 \mathbf{I}$



 $\mathbf{Q}\mathbf{R} = \mathbf{R}\mathbf{K} \text{ with } \mathbf{Q}^T\mathbf{Q} = \alpha^2\mathbf{I}$ $\mathbf{R}^{-1}\mathbf{Q}\mathbf{R} = \mathbf{K}$



 $\mathbf{Q}\mathbf{R} = \mathbf{R}\mathbf{K} \text{ with } \mathbf{Q}^T\mathbf{Q} = \alpha^2 \mathbf{I}$ $\mathbf{R}^{-1}\mathbf{Q}\mathbf{R} = \mathbf{K}$

• K and Q have same characteristic polynomial $d(\lambda) = \det(\mathbf{K} - \lambda \mathbf{I}) = \det(\mathbf{Q} - \lambda \mathbf{I})$



 $\mathbf{Q}\mathbf{R} = \mathbf{R}\mathbf{K} \text{ with } \mathbf{Q}^T\mathbf{Q} = \alpha^2\mathbf{I}$ $\mathbf{R}^{-1}\mathbf{Q}\mathbf{R} = \mathbf{K}$

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and thus agree in eigenvalues and determinant.



Diagonalizing rotation Q

$$\begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ j & -j \end{bmatrix} \begin{bmatrix} e^{j\theta} & 0 \\ 0 & e^{-j\theta} \end{bmatrix} \begin{bmatrix} 1 & j \\ 1 & -j \end{bmatrix}$$
$$= \mathbf{J}_2^{-1} \mathbf{\Delta} \mathbf{J}_2$$



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Different eigenvalue structure for even and odd dimensionality

 $\Delta = \begin{bmatrix} e^{j\theta_1} & & \\ & e^{j\theta_2} & \\ & & e^{-j\theta_2} & \\ & & \ddots \end{bmatrix} \Delta = \begin{bmatrix} 1 & & \\ & e^{j\theta_1} & & \\ & & e^{-j\theta_1} & \\ & & \ddots \end{bmatrix}$ **With analogue block-wise construction of J**_n Steven Bergner et al. - Sampling Lattices with Similarity Scaling Relationships - SampTA 2009

Diagonalizing rotation Q

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$$= \mathbf{J}_2^{-1} \mathbf{\Delta} \mathbf{J}_2$$

Different eigenvalue structure for even and odd dimensionality restricts characteristic polynomial:

- *n* even: $d(\lambda) = \lambda^n + C\lambda^{\frac{n}{2}} + \alpha^n$ with $C^2 < 4\alpha^n$
- $n \text{ odd: } d(\lambda) = \lambda^n \alpha^n$



• Fulfill conditions implied by $\mathbf{QR} = \mathbf{RK}$



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• Companion matrix
$$\mathbf{K} = \begin{bmatrix} 0 & -c_0 \\ 1 & 0 & -c_1 \\ & 1 & 0 & \vdots \\ & \ddots & \ddots & -c_{n-2} \\ & & 1 & -c_{n-1} \end{bmatrix}$$



- Fulfill conditions implied by $\mathbf{QR} = \mathbf{RK}$
- Exhaustive search over range of $\mathbf{K} \in \mathbb{Z}^{n \times n}$
- Companion matrix $\mathbf{K} = \begin{bmatrix} 0 & & -c_0 \\ 1 & 0 & & -c_1 \\ & 1 & 0 & & \vdots \\ & & \ddots & \ddots & -c_{n-2} \\ & & & 1 & -c_{n-1} \end{bmatrix}$
- More with unimodular similarity transforms $\mathbf{K}_T = \mathbf{T}^{-1}\mathbf{K}\mathbf{T}$ with det $\mathbf{T} = 1$ and $\mathbf{T} \in \mathbb{Z}^{n \times n}$



Results

2D



Dilation factor $|\det \mathbf{K}| = 2$



k

Dilation factor $|\det \mathbf{K}| = 3$

1



Rotational grid summary

- First time low-rate admissible dilation matrices are available for n>2
- Additional degrees of freedom in the design enable further optimization
- Current results allow optimized constructions up to n=9



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Data taxonomy

- primary: field measurements
- secondary: synthetic data or human input
- *tertiary*: rules provided by theoretical study or statistical inference



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User input

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Theoretical input

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