Robust Fitting on Poorly Sampled Data for Surface Light Field Rendering and Image Relighting

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Kenneth Vanhoey
KVanhoey@unistra.fr

Basile Sauvage
Sauvage@unistra.fr

Olivier Génevaux
Genevaux@unistra.fr

Frédéric Larue
FLarue@unistra.fr

Jean-Michel Dischler
Dischler@unistra.fr

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Telecom ParisTech, Paris

IGG team, ICube laboratory
Université de Strasbourg / CNRS
OUTLINE

1. Introduction

2. Robust Reconstruction Method

3. Statistical Robustness Analysis

4. Results and conclusion
INTRODUCTION
3D data acquisition with aspect

**Definition**

Recreate a 3D model of a real object through physical acquisition

- Shape (surface)
- Aspect (surface color)

**Examples: geometry**
3D data acquisition with aspect

**Definition**

Recreate a 3D model of a real object through physical acquisition

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- Aspect (surface color)

**Examples: diffuse color**
3D DATA ACQUISITION WITH ASPECT

**Definition**

Recreate a 3D model of a real object through physical acquisition

- Shape (surface)
- Aspect (surface color)

**Examples: Diffuse Color vs. Directional Colors**
## Applications

<table>
<thead>
<tr>
<th><strong>Filing (heritage)</strong></th>
<th><strong>Off-site study</strong></th>
<th><strong>Virtual environments</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Buildings</td>
<td>Experts</td>
<td>Cinema</td>
</tr>
<tr>
<td>Historical objects</td>
<td>Amateurs (art gallery)</td>
<td>Gaming</td>
</tr>
</tbody>
</table>

### Different needs

- Shape
- Aspect
Acquisition and reconstruction process

Physical acquisition

Algorithms

1. Picture projection on mesh
2. Aspect as a light field
ACQUISITION AND RECONSTRUCTION PROCESS

Physical acquisition

1. Picture projection on mesh
2. Aspect as a light field
**Physical Constraints**

- Light-weight, transportable devices: mobile scanner and hand-held camera
- Constrained space: fixed objects, obstacles, ...

**Global Input**

- incomplete coverage
- unstructured coverage

**LF Representation**

- LF Rendering [LH96] / Lumigraph [GGSC96]
- View-Dependant Texture Mapping [DTM96]
- Surface Light Field
  - Through factorization (global) [CBCG02]
  - Per surface unit (local) [WAA+00]

**Local Input**

- poor sampling distribution
- sparse
- noisy
Physical Constraints

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LF Representation

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Local Input

- poor sampling distribution
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- noisy

Context: 3D data acquisition
Acquisition and reconstruction process
Challenges and framework

Introduction
Robust Reconstruction
Statistical Robustness Analysis
Results and conclusion
**Input:** \(K\) color samples

\[\{(\omega_i, v_i)\}\]

\(\omega_i\) is a local observation direction; \(v_i\) is a color.

**Reconstruction algorithm**

\[f(\omega_i) \approx v_i\]

**Output:** light field function

\[f(\omega) = \sum c_j \phi_j(\omega)\]

where the coefficients \(c_j\) are to be estimated.
Contributions

1. Simple Robust Reconstruction Method

2. Analysis / Comparison Tool
Robust Reconstruction Method
Examples

Stabilization through energy minimization

Stabilization energy choice

Examples

Stabilization energy choice

Examples

Vanhoey, Sauvage, Génevaux, Larue, Dischler

Robust Fitting on Poorly Sampled Data for IBR
**Least Squares on Square Error**

\[ \text{ArgMin}_C(E_{MSE}) \]

where \( E_{MSE} = \sum_i \| f(\omega_i) - v_i \|^2 \)

**Fitting**

Which solution to choose?

**Problems**

- Under-constriction
- Non-covered parts
- Perturbations (noise)

**Consequences**

- Several solutions
- Unexpected solutions
- Unstable result
LEAST SQUARES ON SQUARE ERROR

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FITTING

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**Problems**

- Under-construction
- Non-covered parts
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**Generic and Simple Method For:**

- well constrained
- penalizing unexpected colors
- increasing stability w.r.t. perturbations

**Consequences**

- Several solutions
- Unexpected solutions
- Unstable result
**Minimization of weighted energies**

\[ \text{ArgMin}_C((1 - \lambda)E_{MSE} + \lambda E_{stab}) \]

where \( E_{MSE} = \sum_i ||f(\omega_i) - v_i||^2 \)

**Generic and simple method for:**

- well constrained
- penalizing unexpected colors
- increasing stability w.r.t. perturbations

**Problems**

- Under-constriction
- Non-covered parts
- Perturbations (noise)

**Consequences**

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**Minimization of weighted energies**

\[
\text{ArgMin}_C ((1 - \lambda) E_{\text{MSE}} + \lambda E_{\text{stab}})
\]

**E₀ : function energy**

\[
E_{\text{stab}} = E_0 = \int \int_{\Omega} \| f \|^2
\]

Defined in [LLW06] for:

- reducing compression noise
- Spherical Harmonics

**Does not suit our purpose**

Pulls function values towards 0.

\[E_{\text{stab}} = E_0\]
Minimization of weighted energies

\[ \text{ArgMin}_C((1 - \lambda)E_{MSE} + \lambda E_{stab}) \]

\( E_2 : \text{thin-plate energy} \)

\[ E_{stab} = E_2 = \iint_{\Omega} (\Delta f)^2 \]

Defined in [WAA+00] for:

- local under-constriction problem
- Lumispheres

Efficient, but ... 

- Generates expected colors in most cases
- Does not penalize extrapolations
Minimization of weighted energies

\[ \text{ArgMin}_C ((1 - \lambda) E_{\text{MSE}} + \lambda E_{\text{stab}}) \]

**E\textsubscript{1} : gradient energy**

\[ E_{\text{stab}} = E_{\text{1}} = \int \int_\Omega \| \nabla f \|^2 \]

Defined for:
- Limit high frequency variations and extrapolations

**Efficient, and ...**

- Generates expected colors
- Disallows extrapolations
- Tends towards constant value
Part 3 / 4

Statistical Robustness Analysis
**Precision measure**

- Visual
- \[ E_{MSE} = \sum_i \| f(\omega_i) - v_i \|^2 \]

**Stability measure**

A stable fitting algorithm is one that is not sensitive to difficult conditions, e.g.:

- poor sampling conditions (bad coverage, sparsity)
- perturbations (input data noise, missing observation directions)
**Precision measure**

- Visual
- \[ E_{MSE} = \sum_i \| f(\omega_i) - v_i \|^2 \]

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- Visual
- $E_{MSE} = \sum_i \| f(\omega_i) - v_i \|^2$

**Stability measure**

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MEASURES

- Precision error (bias)
- Stability error (variance)
- Expected prediction error $\hat{E}$

EXPECTED PREDICTION ERROR

Noisy input samples

$\lambda = 0.00$

$\lambda = 0.10$

$\lambda = 0.99$
Computation & interpretation

**Tool**

- Analyzing stabilization behavior w.r.t. input data, function basis, basis size, ...
- Derive optimal $\lambda$
- Compare energies

**Estimate $\hat{E}$**

Specific conditions [HTF01]

- No statistical model of input data (noise)
- Scarcity (finite data set to run statistical process on)

Bootstrap method
Results and conclusion
NEED FOR STABILIZATION

(c) ULS

(d) CLS
**Energy Comparison**

**Comparison Results**
All energies generate stable fittings.
- $E_0$ generates unwanted colors
- $E_1$ generates expected colors
- $E_2$ generates expected colors in some conditions

**Robustness of $E_1$**
- Function basis
- Color space
- Sparsity
- Basis size

$E_0$ generates unwanted colors. $E_1$ generates expected colors. $E_2$ generates expected colors in some conditions.
**Energy Comparison**

All energies generate stable fittings.

- $E_0$ generates unwanted colors
- $E_1$ generates expected colors
- $E_2$ generates expected colors in some conditions

**Robustness of $E_1$**

- Function basis
- Color space
- Sparsity
- Basis size
λ CHOICE

**Choose λ**
- Small enough for precision
- High enough for stability

**For our setting**
- $\lambda \in [0.01, 0.05]$ for $E_0$ and $E_1$
- $\lambda \in [0.001, 0.005]$ for $E_2$

**Setting-dependent**
Run bootstrap to derive your own optimal $\lambda$
**Generic method**

Works for any type of hemispherical functions.
**Conclusion**

Robust reconstruction method for surface light fields and image-based relighting applications

- difficult conditions (sparsity, distribution, noise, basis type and size)
- compromise between precision and stability

Statistical tool

- derive an optimal precision/stability compromise
- assess results

**Future work**

Reliable data for post-processing

- simplification
- level-of-detail visualization
- interpolation (for mip-mapping)

Issue

- holes: how to fill them?
Thank you for your attention!

Questions?

Paper available

- soon in Computer Graphics Forum
- now at http://dpt-info.u-strasbg.fr/~kvanhoey

Trevor Hastie, Robert Tibshirani, and Jerome Friedman. 
*The Elements of Statistical Learning.*

Ping-Man Lam, Chi-Sing Leung, and Tien-Tsin Wong. 
Noise-resistant fitting for spherical harmonics. 

Surface light fields for 3d photography. 