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

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« De l’acquisition à la compression des objets 3D »
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Porquerolles
Introduction

Robust Reconstruction

Statistical Robustness Analysis

Results and conclusion

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**

![Example image of 3D objects and cubes](image-url)
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**

![Image of a 3D model with a wooden dragon and dice.]
3D data acquisition with aspect

**Definition**

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

- Shape (surface)
- Aspect (surface color)

**Examples: vs. directional color**
APPLICATIONS

**FILING (HERITAGE)**
- Buildings
- Historical objects

**OFF-SITE STUDY**
- Experts
- Amateurs (art gallery)

**VIRTUAL ENVIRONMENTS**
- Cinema
- Gaming

**DIFFERENT NEEDS**
- Shape
- Aspect
Physical acquisition

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

PHYSICAL ACQUISITION

ALGORITHMS

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, ...

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**Global Input**

- incomplete coverage
- unstructured coverage

**LF Representation**

Radiance function per surface unit.

**Local Input**

- poor sampling distribution
- sparse
- noisy
**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

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

Introduction
Robust Reconstruction
Statistical Robustness Analysis
Results and conclusion
Robust Reconstruction Method
EXAMPLES
**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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**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
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**Problems**
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**Minimization of weighted energies**

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

**\( E_0 : \text{function energy} \)**

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

Defined in [LLW06] for:
- reducing compression noise
- Spherical Harmonics

**Does not suit our purpose**

Pulls function values towards 0.
Minimization of Weighted Energies

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

\( E_2 : \) Thin-Plate Energy

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

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

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

\[ E_{stab} = E_1 = \int\int_{\Omega} \| \nabla f \|^2 \]

Defined for:
- limiting high frequency variations and extrapolations

Efficient, and . . .
- Generates expected colors
- Disallows extrapolations
- Tends towards constant value
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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Measures

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

Expected prediction error

![Graph showing the relationship between expected prediction error and input samples for different values of $\lambda$. The graph illustrates the trade-off between precision and stability.]
Computation & interpretation

Example

Tool

- Analyzing stabilization behavior w.r.t. input data, function basis, basis size, ...
- Derive optimal $\lambda$
- Compare energies
Robust Fitting on Poorly Sampled Data for IBR
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
ENERGY COMPARISON

Comparison results

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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 \( \lambda \)
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?
Merci

Questions?

Où trouver l’article

- early view de *Computer Graphics Forum*
- via http://dpt-info.u-strasbg.fr/~kvanhoey

