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

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Outline

Part 1 / 4

Introduction

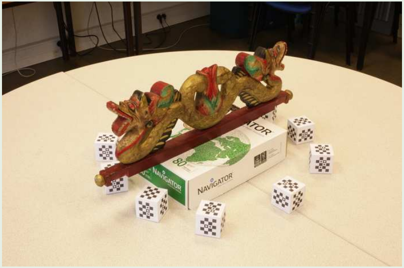
3D data acquisition with aspect

Definition

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

- Shape (surface)
- Aspect (surface color)

Examples : geometry



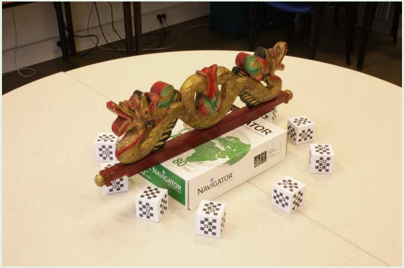
3D data acquisition with aspect

Definition

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

- Shape (surface)
- Aspect (surface color)

Examples : diffuse color



3D data acquisition with aspect

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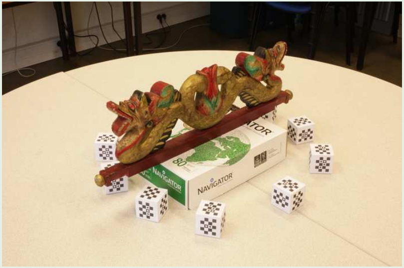
Recreate a 3D model of a real object through physical acquisition

- Shape (surface)
- Aspect (surface color)

Examples : diffuse color vs. directional colors



Applications

Filing (heritage)

- Buildings
- Historical objects

Off-site study

- Experts
- Amateurs (art gallery)

Virtual environments

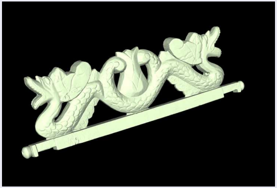
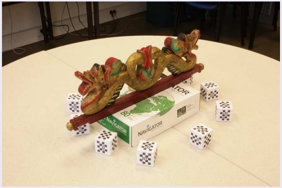
- Cinema
- Gaming

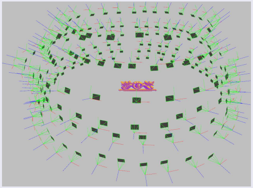
Different needs

- Shape
- Aspect

Acquisition and reconstruction process

Physical acquisition

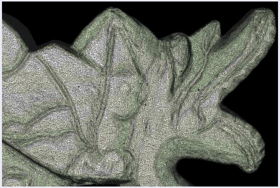
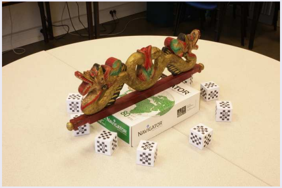
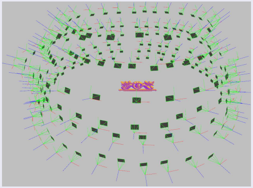


Algorithms

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

Acquisition and reconstruction process

Physical acquisition

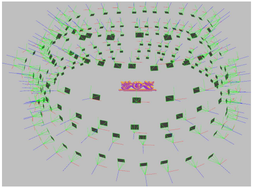




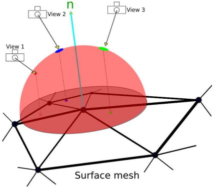
Algorithms

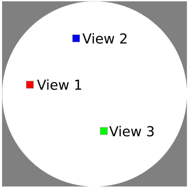
1. Picture projection on mesh
2. Aspect as a light field

Physical constraints

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







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

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- Light-weight, transportable devices : mobile scanner and hand-held camera
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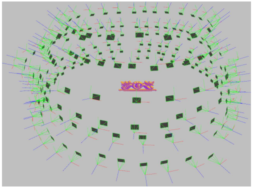

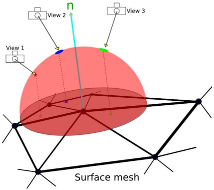

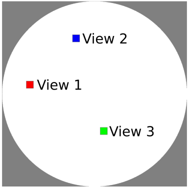

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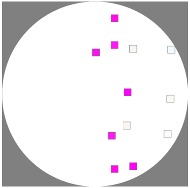
Input : K color samples

$$\{(\omega_i, v_i)\}$$

ω_i is a local observation direction ;
v_i is a color.



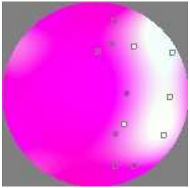
Reconstruction algorithm

$$f(\omega_i) \approx v_i$$

Output : light field function

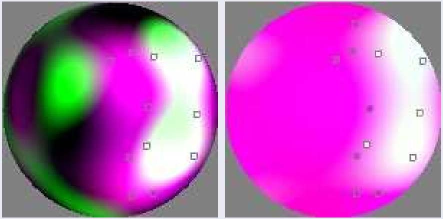
$$f(\omega) = \Sigma c_j \phi_j(\omega)$$

where the coefficients c_j are to be estimated.

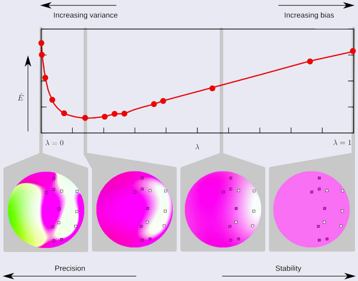


Contributions

1. Simple robust reconstruction method



2. Analysis / comparison tool



Part 2 / 4

Robust Reconstruction Method

Examples

Least Squares on square error

$$ArgMin_C(E_{MSE})$$

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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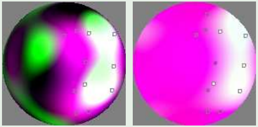

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Generic and simple method for :

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

Problems

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

Consequences

- Several solutions
- Unexpected solutions
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Minimization of weighted energies

$$ArgMin_C((1-\lambda)E_{MSE} + \lambda E_{stab})$$

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

Generic and simple method for :

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Minimization of weighted energies

$$ArgMin_C((1-\lambda)E_{MSE} + \lambda E_{stab})$$

E_0 : function energy

$$E_{stab} = E_0 = \iint_{\Omega} \|f\|^2$$

Defined in [LLW06] for :

- reducing compression noise
- Spherical Harmonics

Does not suit our purpose

Pulls function values towards 0.

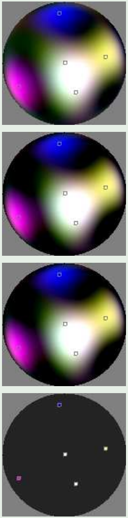
$E_{stab} = E_0$

$\lambda = 0$

$\lambda = 0.05$

$\lambda = 0.1$

$\lambda = 1$



Minimization of weighted energies

$$ArgMin_C((1-\lambda)E_{MSE} + \lambda E_{stab})$$

E_2 : thin-plate energy

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

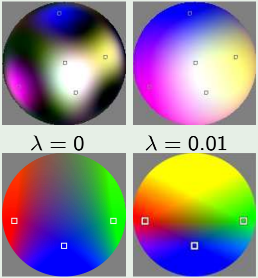
Defined in [WAA$^+$00] for :

- local under-constriction problem
- Lumispheres

Efficient, but ...

- Generates expected colors in most cases
- Does not penalize extrapolations

$E_{stab} = E_2$



Minimization of weighted energies

$$ArgMin_C((1-\lambda)E_{MSE} + \lambda E_{stab})$$

E_1 : gradient energy

$$E_{stab} = E_1 = \iint_\Omega \|\nabla f\|^2$$

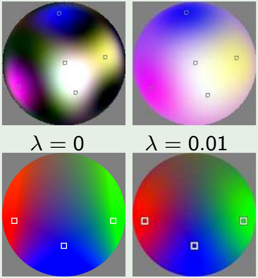
Defined for :

- Limit high frequency variations and extrapolations

Efficient, and ...

- Generates expected colors
- Disallows extrapolations
- Tends towards constant value

$E_{stab} = E_1$



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

Stability measure

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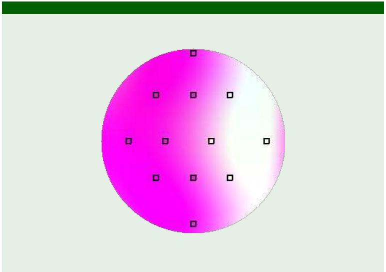

Precision measure

- 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. :

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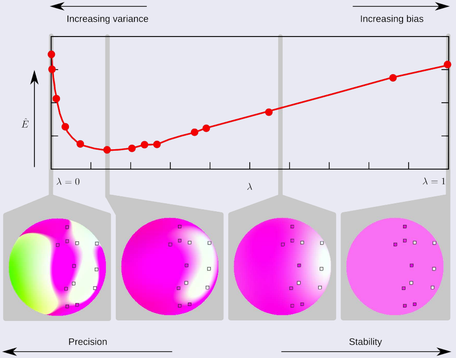
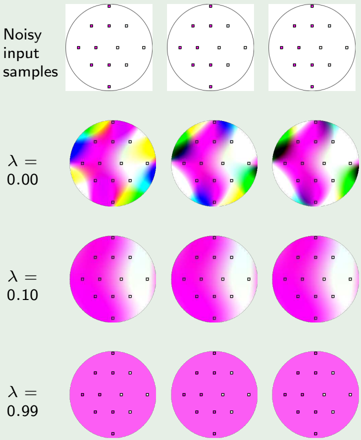
Measures

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

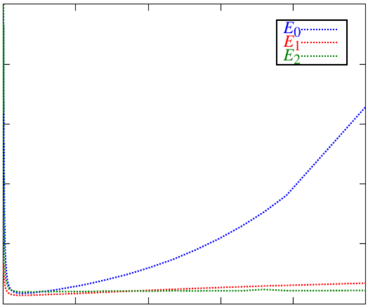
Expected prediction error





Computation & interpretation

Example



Tool

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

Estimate $\hat{E}$

Specific conditions [HTF01]

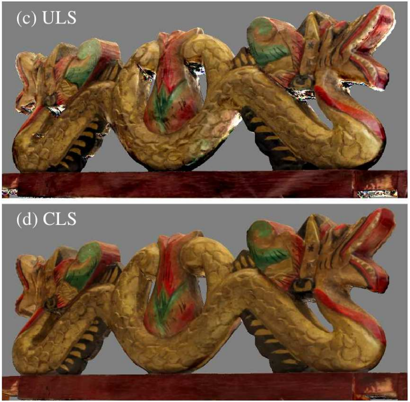
- No statistical model of input data (noise)
- Scarcity (finite data set to run statistical process on)

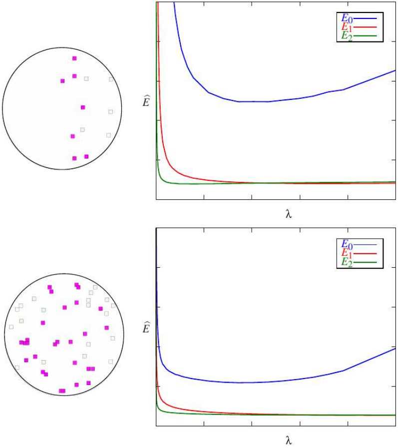
Bootstrap method

Part 4 / 4

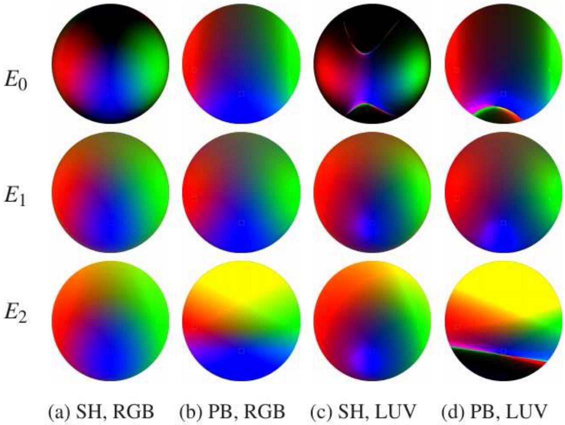
Results and conclusion

Need for stabilization





Energy comparison



Comparison results

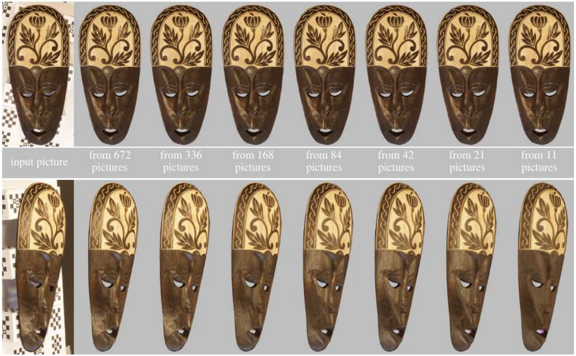
All energies generate stable fittings.

- 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



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Robustness of E_1

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λ choice

Choose λ

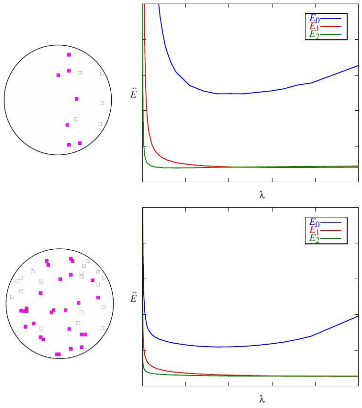
- Small enough for precision
- High enough for stability

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 λ



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.
Springer Series in Statistics. Springer New York Inc., New York, USA, 2001.

Ping-Man Lam, Chi-Sing Leung, and Tien-Tsin Wong.
Noise-resistant fitting for spherical harmonics.
IEEE Transactions on Visualization and Computer Graphics, 12 :254–265, March 2006.

Daniel N. Wood, Daniel I. Azuma, Ken Aldinger, Brian Curless, Tom Duchamp, David H. Salesin, and Werner Stuetzle.
Surface light fields for 3d photography.
In *Proceedings of the 27th annual conference on Computer graphics and interactive techniques*, SIGGRAPH '00, pages 287–296, New York, NY, USA, 2000. ACM Press/Addison-Wesley Publishing Co.