Superresolution Texture Maps for Multiview Reconstruction

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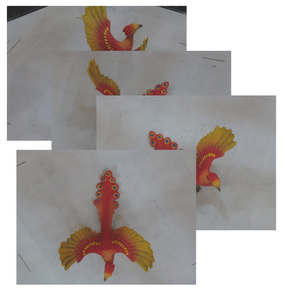
Problem and Contributions

Given: multiple calibrated views of a surface **Find:**



n images $\mathcal{I}_i : \Omega_i \to \mathbb{R}$
projections $\pi_i : \mathbb{R}^3 \to \mathbb{R}^2$

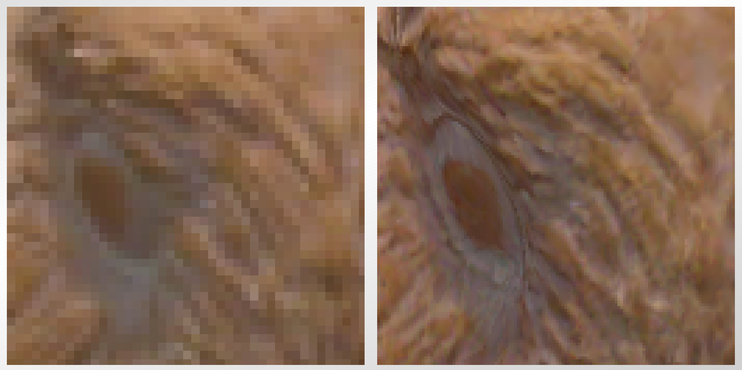
surface $\Sigma \subset \mathbb{R}^3$
(assumed Lambertian)

color texture map
$T : \Sigma \to \mathbb{R}^3$

Idea: Each surface patch is visible in multiple cameras, so excess information can be leveraged to estimate a super-resolved texture map.

Contributions

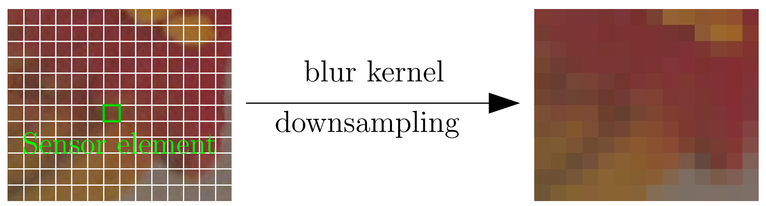
- First variational framework for superresolution on curved surfaces
- Generates excellent texture maps with higher detail than input images
- No problems with seams or blur due to blending of different views



Input Image *Rendered Model*

Superresolution Model

Image formation model: each sensor element samples incoming light over its area, which is modeled by a blur kernel b [4]



Desired texture minimizes energy

$$E(T) := \sum_{i=1}^{n} \underbrace{\int_{\hat{S}_i} \left(b * (T \circ \beta_i) - \mathcal{I}_i\right)^2 \, \mathrm{dx}}_{\text{data term for camera } i} + \underbrace{\int_{\Sigma} \|\nabla_\Sigma T\| \, \mathrm{ds}}_{\text{regularizer}}.$$

Note that the data term is defined in *image space*, while the regularizer is the total variation of the texture map *on the surface*. β_i is the backprojection map, which is the inverse of the projection restricted to the surface region visible in camera i. Thus, $T \circ \beta_i$ is a high-resolution rendering of the surface using the texture map T.

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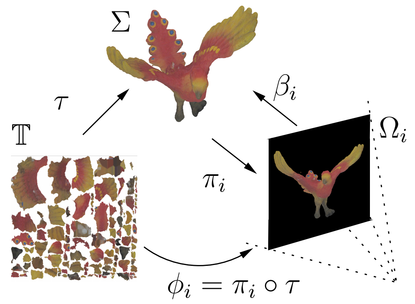
Energy Minimization Framework

Step 1: introduce a conformal atlas which parametrizes the surface.

Conformal atlas

- Chart mappings behave locally like a rotation and scaling by the *conformal factor* λ.
- Minimizes distortions, differential operators on the surface can easily be translated to texture space [3].



Mappings between surface, texture and image space

Step 2: transform Euler-Lagrange equation to texture space to obtain PDE.

Superresolution problem

Find a texture map $\mathcal{T} : \mathbb{T} \to \mathbb{R}$ which satisfies the Euler-Lagrange equation

$$\frac{1}{\lambda}\mathrm{div}\left(\sqrt{\lambda}\frac{\nabla\mathcal{T}}{\|\nabla\mathcal{T}\|}\right) + \sum_{i=1}^{n}\frac{v_i}{\sigma}\left((\mathcal{J}_i\mathcal{D}_i)\circ\phi_i\right) = 0$$

on the chart domains. λ assigns the conformal factor to each point in $\mathbb{T}$, v_i indicates visibility of a texel.

Intensity-coded $\mathcal{J}_i$

$\mathcal{J}_i =$ surface area element with respect to the backprojection

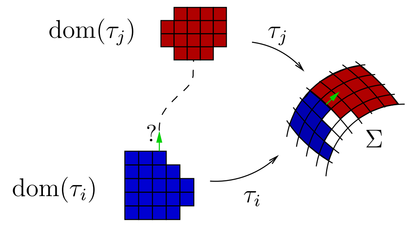
$\mathcal{D}_i =$ derivative of data term

$$\mathcal{D}_i := \bar{b} * \left(b * (T \circ \beta_i) - \mathcal{I}_i\right).$$

Step 3: solve the PDE via gradient descent on texture space.

Numerical implementation

- Functional is *convex*, gradient descent yields globally optimal solution
- Start with texel-wise weighted average as initialisation



Periodic boundary conditions on computation grid

Validation on Synthetic Data

Experiment: Reconstruct a high-resolution texture from 40 low-resolution views of a rendered torus with exact geometry known and measure MSE ϵ.

512×512 input		341×341		256×256		Ground
Init	Result	Init	Result	Init	Result	truth
ϵ=6.35	4.56	8.01	6.07	8.08	6.23	
ϵ=4.17	2.94	4.76	3.04	5.03	3.23	

Superresolution textures from downscaled images are on average more accurate than texel-wise initialization from four times the input resolution.

Results on Real-World Objects

Bird model: 35 views, image resolution 768×584.

Weighted average *Superresolution result* *Input image*

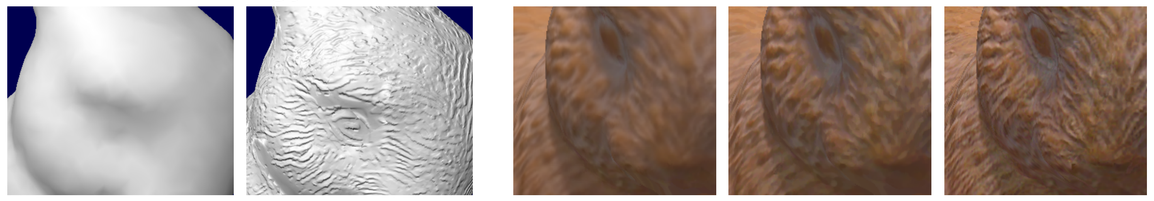
Beethoven model: 35 views, image resolution 768×584.

Weighted average *Superresolution result* *Input image*

Note: Input geometry estimated using algorithm [2], surfaces represented implicitly on about 256^3 voxels. Texture resolution is 2048×2048.

Followup Work: Displacement Maps [1]

Idea: estimate an additional *displacement map* $D : \mathbb{T} \to \mathbb{R}$ by minimizing an extended energy functional.



Original geometry *Estimated displacement* *Weighted average* *Superresolution only* *With displacement*

Result: Displacement map adds high detail to input geometry, which leads to significantly improved texture estimation.

References

[1] B. Goldluecke and D. Cremers. A superresolution framework for high-accuracy multiview reconstruction. In *Pattern Recognition (Proc. DAGM)*, 2009.
[2] K. Kolev and D. Cremers. Integration of multiview stereo and silhouettes via convex functionals on convex domains. In *Proc. ECCV*, volume 5302, pages 752–765, 2008.
[3] L. M. Lui, Y. Wang, and T. F. Chan. Solving PDEs on manifold using global conformal parameterization. In *Proc. VLSM*, pages 309–319, 2005.
[4] F. Sroubek, G. Cristobal, and J. Flusser. A unified approach to superresolution and multichannel blind deconvolution. *IEEE Transactions on Image Processing*, 16(9):2322–2332, 2007.