As-Rigid-As-Possible Stereo under Second Order Smoothness Priors

Chi Zhang[1], Zhiwei Li[2], Rui Cai[2], Hongyang Chao[1], Yong Rui[2]

1 Sun Yat-Sen University, Guangzhou, P.R. China

2 Microsoft Research, Beijing, P.R. China

ECCV '14 Zürich, September 6-12th, 2014

Problem Definition

INPUT: A pair of stereo images
OUTPUT: Dense correspondences, or disparity map

Motivation: Combine Two Priors

Segment-wise *As-Rigid-As-Possible* Prior

- *Pros: Long-Range Constraints*
- *Cons: Bad alignment on boundaries*

Pixel-wise *Second Order Smoothness* Prior

- *Pros: Flexible, has not alignment problem*
- *Cons: Too Local, sometimes over flexible*

Algorithm

Algorithm 1 As-Rigid-As-Possible Stereo

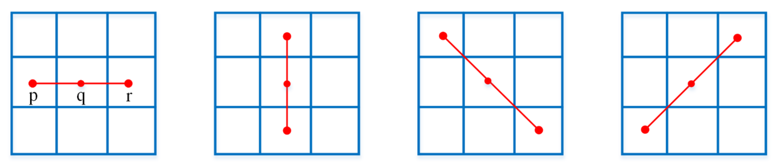
compute Laplacian matrix L_i
set θ to zero
repeat
  repeat
    minimize E_{DATA} w.r.t. $\boldsymbol{\Lambda}$
      by a derivative-free algorithm
    minimize E_{SMOOTH} w.r.t. $\mathbf{u}$
      by sparse Cholesky decomposition
  until converged
  increase θ
until converged

Formulation: Jointly Optimize Quadratic Surface Coefficients and Disparity Map

disparity map — *quadratic surface coefficients* — *2nd order prior* — *data cost with built-in ARAP prior*

$$E_1(\mathbf{u},\boldsymbol{\Lambda}) = \boxed{\mathbf{u}^\top\Big(\sum_i L_i^\top L_i\Big)\mathbf{u}} + \lambda\boxed{\sum_{\mathbf{s}}\sum_{p\in\mathbf{s}}\rho(p, p - D_{\mathbf{s}}(p))} \qquad \boxed{s.t. \quad \mathbf{u} = \mathbf{D}(\boldsymbol{\Lambda})}$$

L_i are four directional Laplacian operators:



Surface equation:
$D_{\mathbf{s}}([x,y]^\top) = dx^2 + ey^2 + ax + by + c$

Relax

$$E_2(\mathbf{u},\boldsymbol{\Lambda}) = \mathbf{u}^\top\Big(\sum_i L_i^\top L_i\Big)\mathbf{u} + \theta(\mathbf{u}-\mathbf{v})^\top G(\mathbf{u}-\mathbf{v}) + \lambda\sum_{\mathbf{s}}\sum_{p\in\mathbf{s}}\rho(p, p - D_{\mathbf{s}}(p))$$

Alternative Optimization

$$E_{\text{DATA}}(\boldsymbol{\Lambda}) = \lambda\sum_{\mathbf{s}}\sum_{p\in\mathbf{s}}\rho(p, p - D_{\mathbf{s}}(p)) + \theta(\mathbf{u}-\mathbf{D}(\boldsymbol{\Lambda}))^\top G(\mathbf{u}-\mathbf{D}(\boldsymbol{\Lambda}))$$

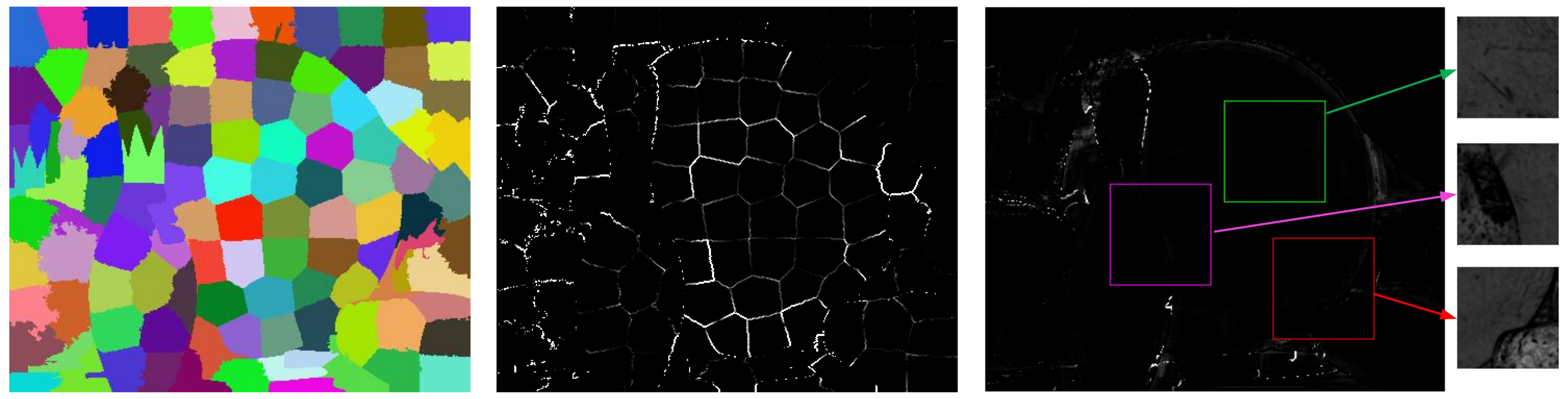
Find new surfaces by PatchMatch-like Nelder-Mead search

$$E_{\text{SMOOTH}}(\mathbf{u}) = \mathbf{u}^\top\Big(\sum_i L_i^\top L_i\Big)\mathbf{u} + \theta(\mathbf{u}-\mathbf{v})^\top G(\mathbf{u}-\mathbf{v})$$

$$\Big(\sum_i L_i^\top L_i + \theta G\Big)\mathbf{u} = \theta G\mathbf{v}$$

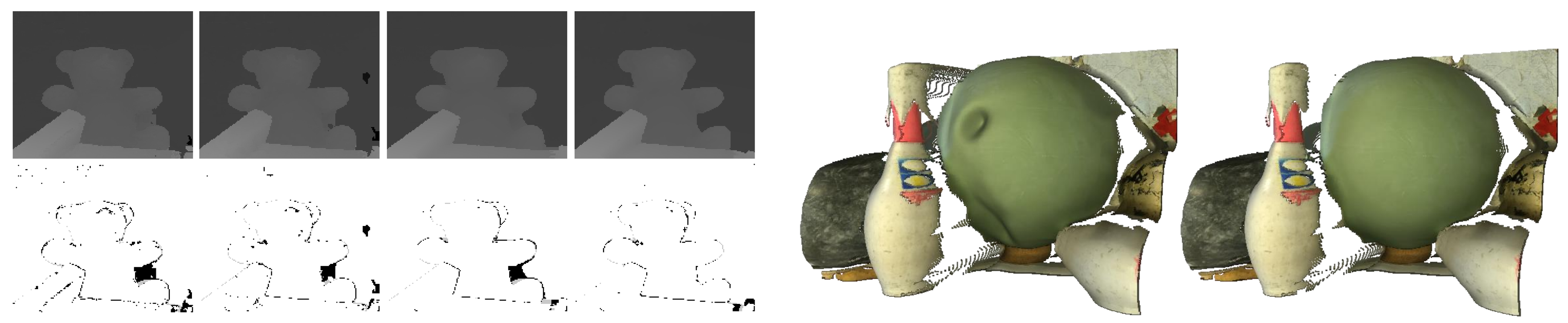
E_{SMOOTH} has closed form solution. But we use gradient decent for speed

Optimization Process



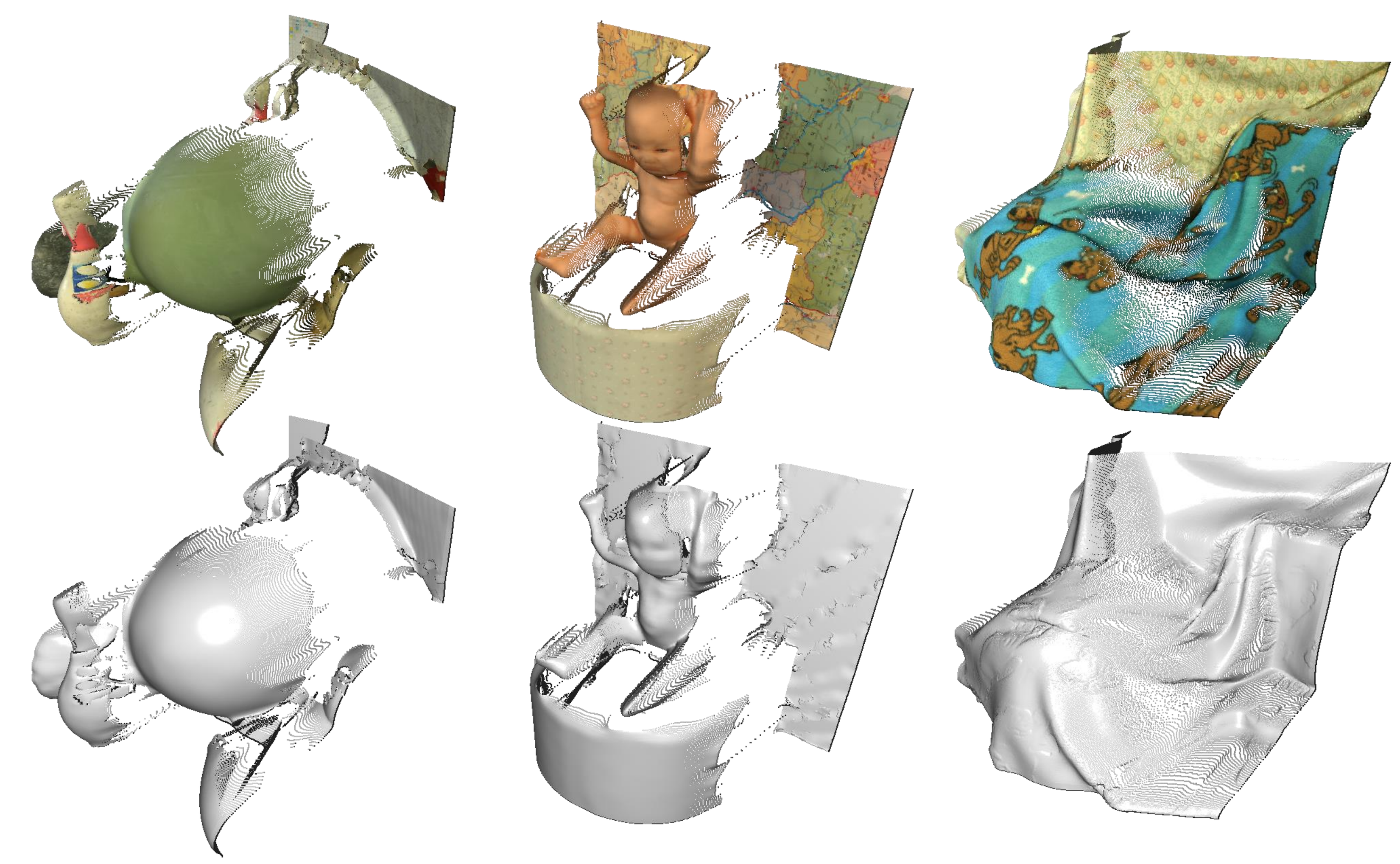
SLIC Segmentation — *2nd order smooth cost before optimization* — *2nd order smooth cost after optimization*

Comparisons



PatchMat. — *PMBP* — *PmHuber* — *Ours* — *PatchMatch* — *Ours*

Point Clouds of Ours



Conclusions

- Two priors complement each other
- Generate “seamless” accurate disparity maps
- Fast global method, 10s per pair