

Progressive Multigrid Eigensolvers for Multiscale Spectral Segmentation

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Spectral Segmentation

Build a weighted graph $G = (V, E, W)$ from the image



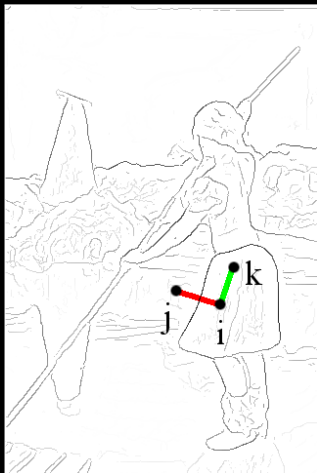
Spectral Segmentation

Build a weighted graph $G = (V, E, W)$ from the image

- Define W using **Intervening Contour**

$$w = \left(\begin{array}{c} j \\ \text{---} \\ i \end{array} \right)$$

(i, j) low affinity



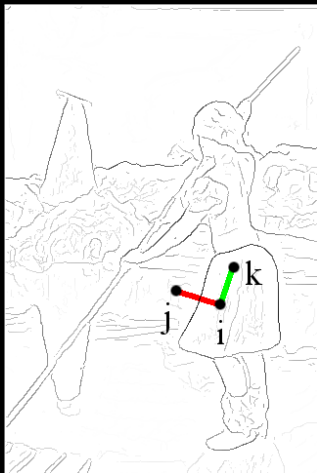
Spectral Segmentation

Build a weighted graph $G = (V, E, W)$ from the image

- ▶ Define W using **Intervening Contour**

$$w = \begin{pmatrix} & k \\ i & \text{green square} \end{pmatrix}$$

(i, k) **high** affinity



Spectral Segmentation

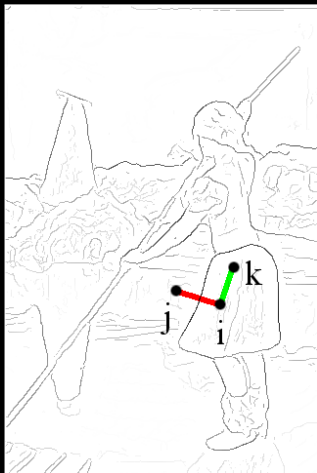
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(i, k) **high** affinity

- Normalized Cuts**
[Shi & Malik 1997]



Normalized Cuts

- ▶ Graph $G = (V, E, W)$
- ▶ Split into A, B disjoint, $A \cup B = V$

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$$cut(A, B) = \sum_{u \in A, v \in B} w(u, v)$$

$$assoc(A, V) = \sum_{u \in A, v \in V} w(u, v)$$

$$Ncut(A, B) = \frac{cut(A, B)}{assoc(A, V)} + \frac{cut(A, B)}{assoc(B, V)}$$

Normalized Cuts

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- ▶ General case: partition using smallest eigenvectors of

$$(D - W)z = \lambda Dz$$

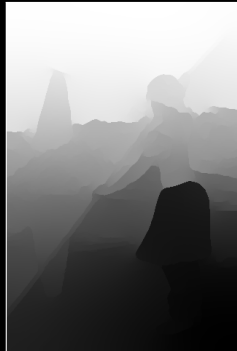
where $D_{ii} = \sum_j W_{ij}$

Normalized Cuts: Embedding

Image

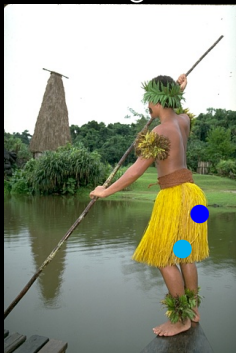


Eigenvector

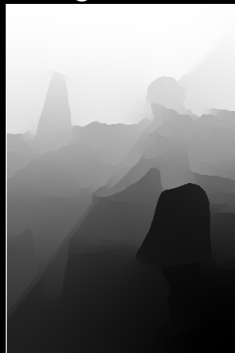


Normalized Cuts: Embedding

Image

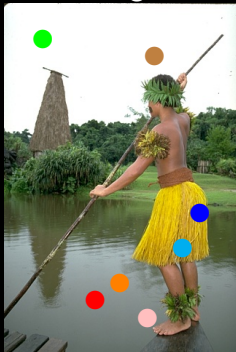


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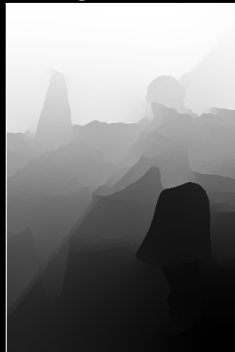


Normalized Cuts: Embedding

Image



Eigenvector

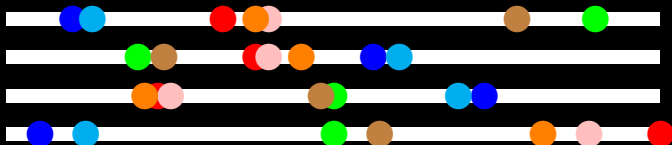
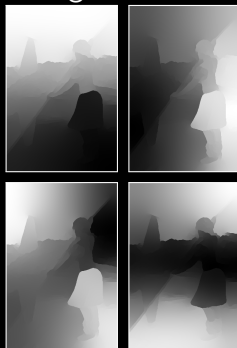


Normalized Cuts: Embedding

Image

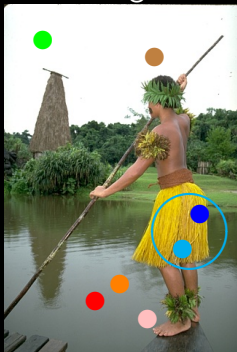


Eigenvectors

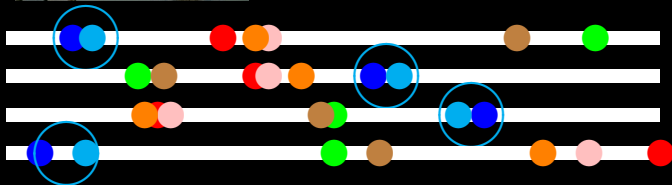
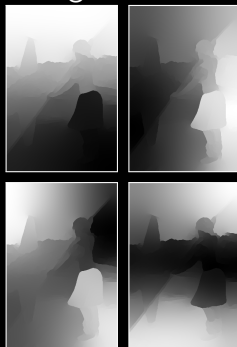


Normalized Cuts: Embedding

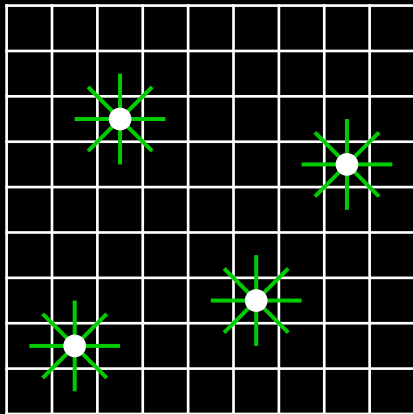
Image



Eigenvectors

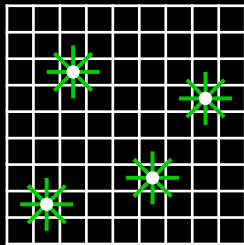


Single Scale Unconstrained Problem



W

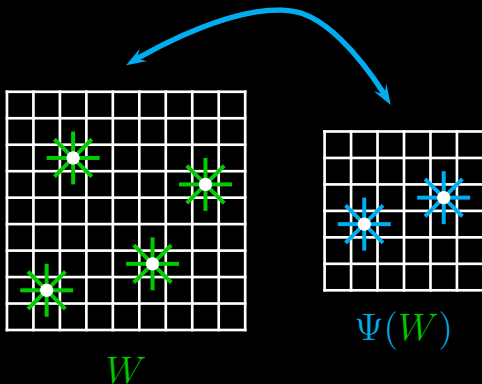
Multigrid Solver



W

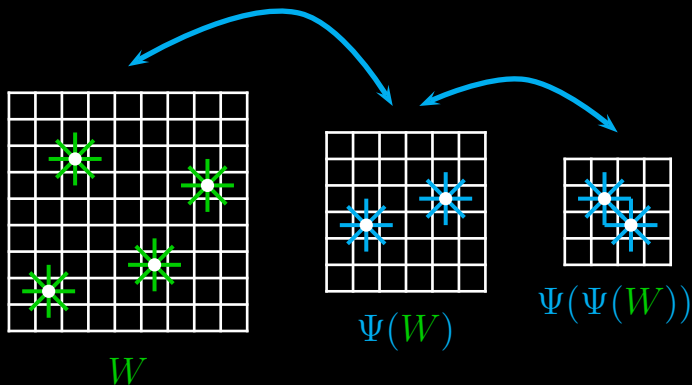
[Chennubhotla and Jepson, NIPS 2005]
[Brezina et al., Num. Linear Alg. w/App., 2008]
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Multigrid Solver

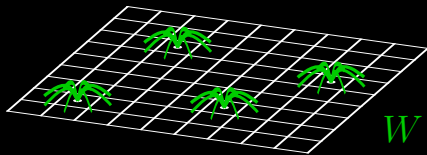


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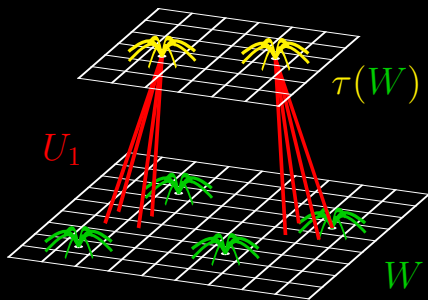
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Multirange Problem



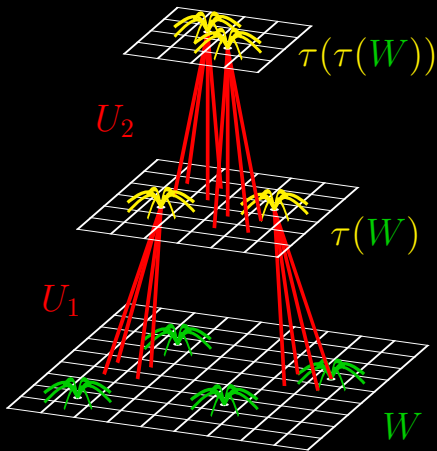
[Cour, Benezit, and Shi, CVPR 2005]

Multirange Problem



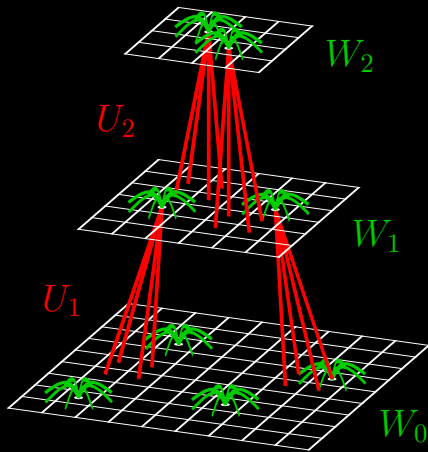
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Multirange Problem



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Multiscale Problem



Multigrid and Multiscale

Multigrid and Multiscale

multigrid: efficient solver computation

Multigrid and Multiscale

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multiscale: efficient problem representation

Multigrid and Multiscale

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multiscale: efficient problem representation

use both!

Multigrid and Multiscale

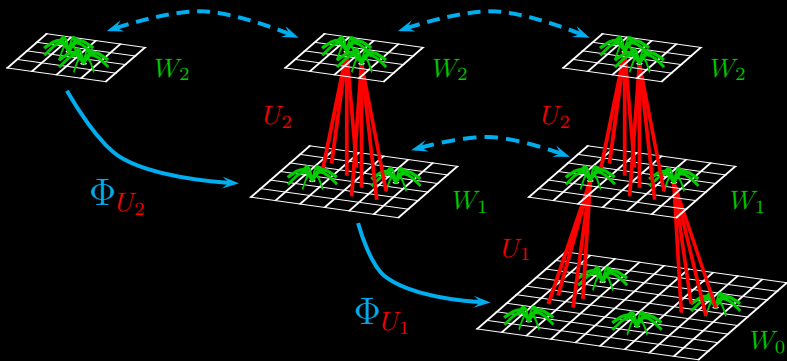
multigrid: efficient solver computation

multiscale: efficient problem representation

use both!

multiscale structure shapes multigrid strategy

Progressive Multigrid Multiscale



Algorithm Overview

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$$W = \begin{bmatrix} W_2 & 0 & 0 \\ 0 & W_1 & 0 \\ 0 & 0 & W_0 \end{bmatrix} \quad U = [0 \quad U_2 \quad U_1] \quad Z = \begin{bmatrix} Z_2 \\ Z_1 \\ Z_0 \end{bmatrix}$$

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$$\widetilde{Z}_1 = \widetilde{U}_2 (\widetilde{U}_2^* \widetilde{U}_2)^{-1} (-\widehat{U}_2^* \bar{Z}_2)$$

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- ▶ Least-squares interpolate:
$$\widetilde{Z}_1 = \widetilde{U}_2 (\widetilde{U}_2^* \widetilde{U}_2)^{-1} (-\widehat{U}_2^* \bar{Z}_2)$$
- ▶ Use $[\bar{Z}_2; \widetilde{Z}_1]$ as initial guess for solving:
$$(\text{Diag}(W_2, W_1), [0 \quad U_2]) \text{ for } [\bar{Z}_2; \bar{Z}_1]$$

Implementation

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- ▶ **Randomized Matrix Approximation**
[Halko, Martinsson, and Tropp, SIREV, 2011]

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- ▶ ~~Work with m eigenvectors simultaneously~~
- ▶ Work with $n \times 2m$ intermediate representation:
 - $n = \#$ nodes
 - $m = \#$ eigenvectors
- ▶ n increases coarse-to-fine
- ▶ **Randomized Matrix Approximation**
[Halko, Martinsson, and Tropp, SIREV, 2011]
 - ▶ Randomized algorithms for linear algebra problems
 - ▶ Exponentially small failure probability
 - ▶ Simple implementation
 - ▶ Same computational complexity
 - ▶ Better hardware parallelization properties

Randomized Matrix Approximation

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► Fixed Rank Problem

Given: $n \times n$ sparse matrix M

Find: $n \times l$ dense matrix A , where $l = 2m \ll n$

Such that: range of A approximates range of M

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► Randomized Subspace Iteration

Draw draw $n \times l$ Gaussian matrix Ω

$$Y \leftarrow (MM^*)^q M\Omega$$

$$A \leftarrow \text{QR-ORTHONORMALIZE}(Y)$$

Randomized Matrix Approximation

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► Eigensolver

$$B \leftarrow A^* M A$$

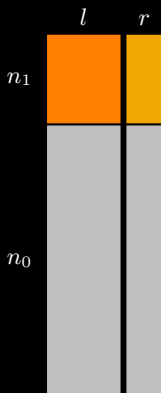
$$(V, \Lambda) \leftarrow \text{EIGS}(B, m)$$

$$Z \leftarrow AV$$

$l \times l$ matrix
small eigenproblem

Matrix Approximation + Interpolation

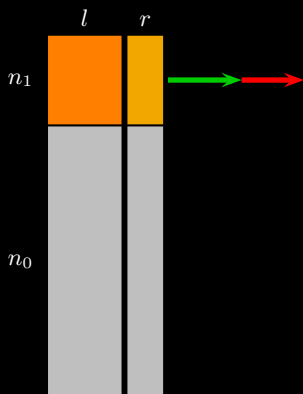
$$M = QPQ$$



Initialize A

Matrix Approximation + Interpolation

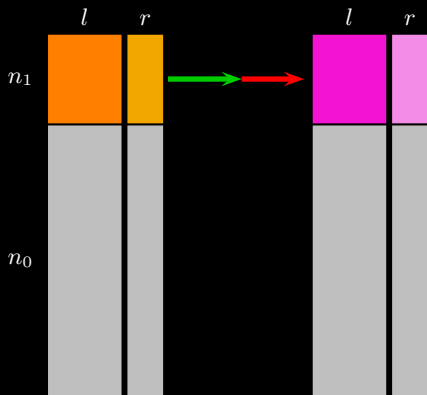
$$M = QPQ$$



Apply M (Coarse)

Matrix Approximation + Interpolation

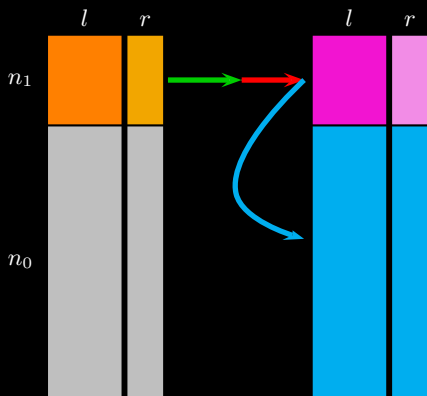
$$M = QPQ$$



Converge A (Coarse)

Matrix Approximation + Interpolation

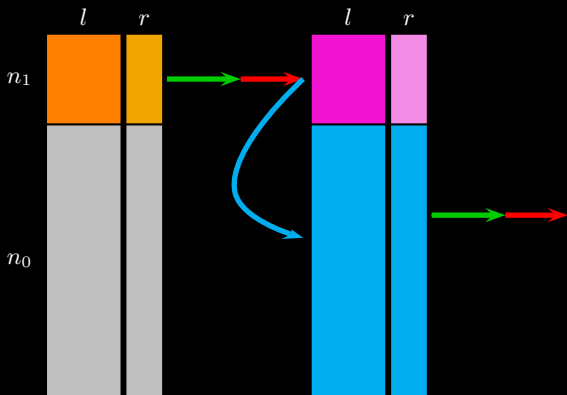
$$M = QPQ$$



Interpolate

Matrix Approximation + Interpolation

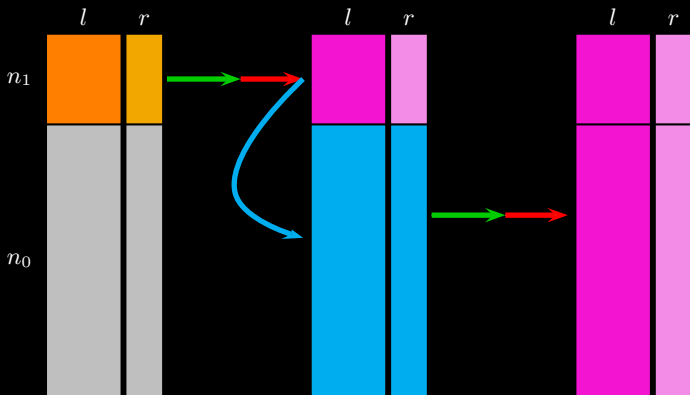
$$M = QPQ$$



Apply M (Fine)

Matrix Approximation + Interpolation

$$M = QPQ$$



Converge A

Eigenvector Convergence Comparison



Image

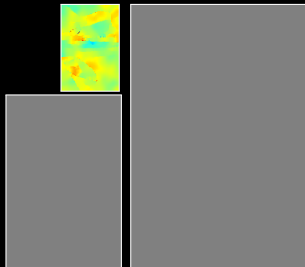
Eigenvector 7

Eigenvector Convergence Comparison

1 coarse: 0.46 sec



Image



Progressive Multigrid

Eigenvector 7

Eigenvector Convergence Comparison

20 coarse: 3 sec



Image



Progressive Multigrid

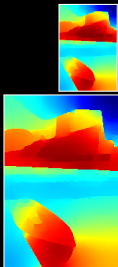
Eigenvector 7

Eigenvector Convergence Comparison

20 c, 1 med: 5 sec



Image



Progressive Multigrid



Eigenvector 7

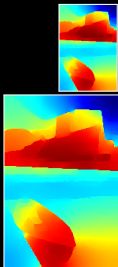
Eigenvector Convergence Comparison

20 c, 1 med: 5 sec

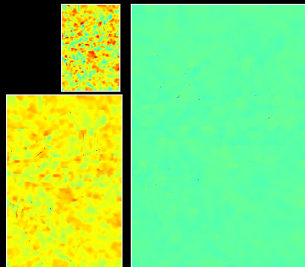
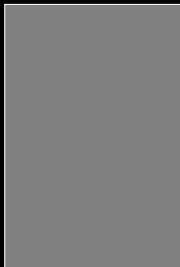
1 fine: 15 sec



Image



Progressive Multigrid



Baseline Solver

Eigenvector 7

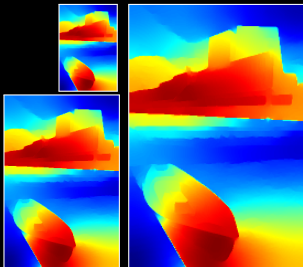
Eigenvector Convergence Comparison

..., 1 fine: 17 sec

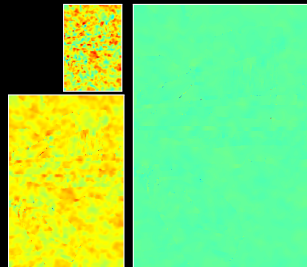
1 fine: 15 sec



Image



Progressive Multigrid



Baseline Solver

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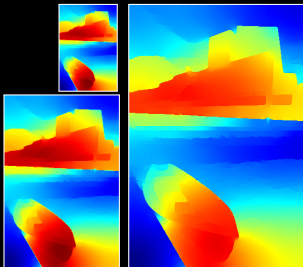
Eigenvector Convergence Comparison

..., 3 fine: **27 sec**

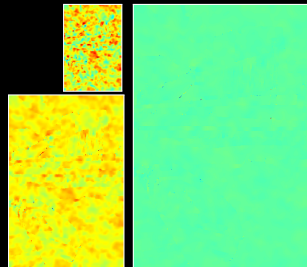
1 fine: 15 sec



Image



Progressive Multigrid



Baseline Solver

Eigenvector 7

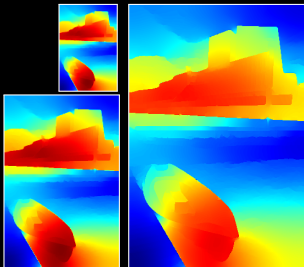
Eigenvector Convergence Comparison

..., 3 fine: **27 sec**

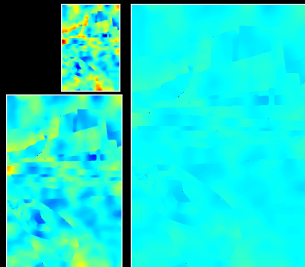
5 fine: 34 sec



Image



Progressive Multigrid



Baseline Solver

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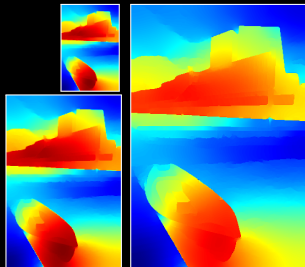
Eigenvector Convergence Comparison

..., 3 fine: **27 sec**

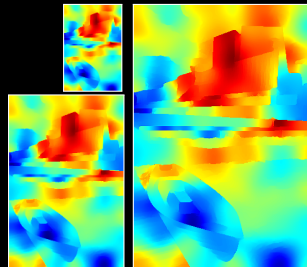
20 fine: 94 sec



Image



Progressive Multigrid



Baseline Solver

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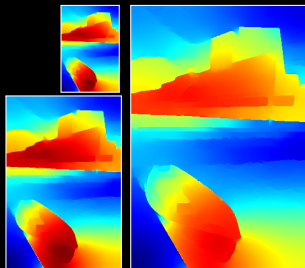
Eigenvector Convergence Comparison

..., 3 fine: **27 sec**

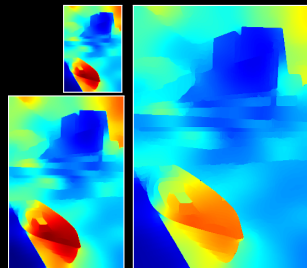
50 fine: 202 sec



Image



Progressive Multigrid



Baseline Solver

Eigenvector 7

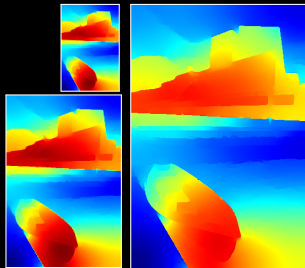
Eigenvector Convergence Comparison

..., 3 fine: **27 sec**

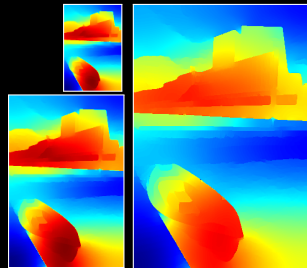
225 fine: **760 sec**



Image



Progressive Multigrid



Baseline Solver

Eigenvector 7

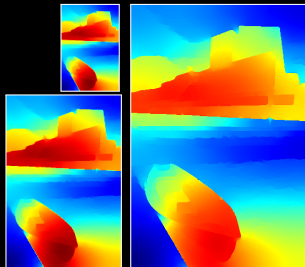
Eigenvector Convergence Comparison

..., 3 fine: **27 sec**

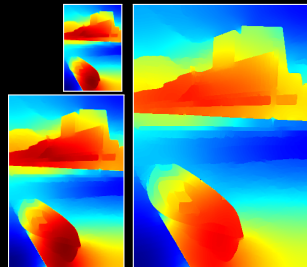
225 fine: **760 sec**



Image



Progressive Multigrid



Baseline Solver

Eigenvector 7

> 10× speedup

Multiscale Spectral Pb

Image



sPb



M-sPb Coarse



M-sPb Medium



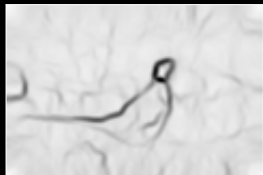
M-sPb Fine

Multiscale Spectral Pb

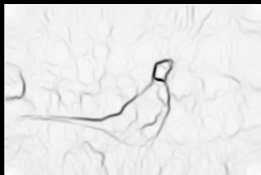
Image



sPb



M-sPb Coarse



M-sPb Medium



M-sPb Fine

Multiscale Spectral Pb

Image



sPb



M-sPb Coarse



M-sPb Medium



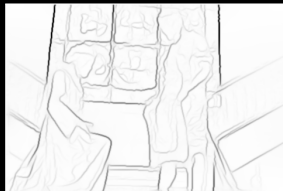
M-sPb Fine

Multiscale Spectral Pb

Image



sPb



M-sPb Coarse



M-sPb Medium

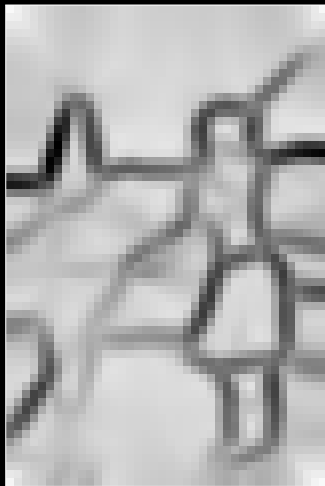


M-sPb Fine

Multiscale Alignment for Free



Image



Multiscale sPb 1

Multiscale Alignment for Free



Image



Multiscale sPb 2

Multiscale Alignment for Free



Image

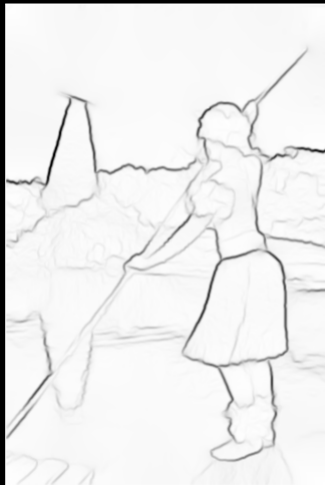


Multiscale sPb 3

Multiscale Alignment for Free



Image



Multiscale sPb 4

Multiscale Alignment for Free



Image



Multiscale sPb 5

Thank You