Exploring Disk-Shaped Corner Regions as Seed Points for PDE-based Inpainting

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Motivation

What is inpainting…

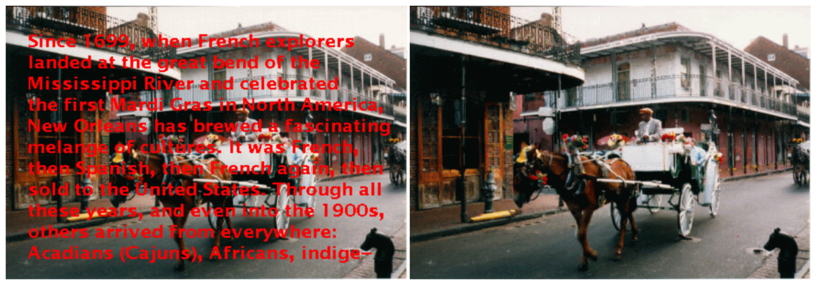

Figure 1: Example for an application of inpainting in image restoration [Bertalmio et al., 2000]

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- "Filling in" of areas without having to know the data in these regions
- Digital inpainting introduced around 2000 (e.g. [Bertalmio et al., 2000, Masnou and Morel, 1998])

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Inpainting based image compression methods are already able to outperform traditional codecs like JPEG for high compression rates

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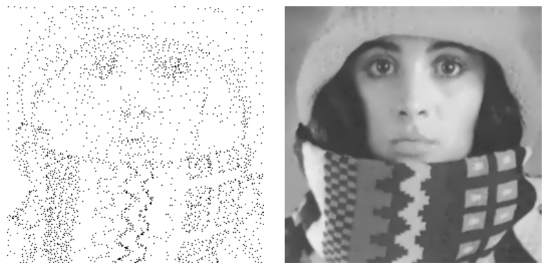

Figure 2: Mask and respective reconstruction [Hoeltgen et al., 2016]

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- Many different approaches (semantic, tree-based, analytic, …)
- **Semantic:** Image features as seed points (edges/corners)
- Edge-based methods successful [Mainberger et al., 2011]
- Corners as seed points barely explored

Previous Work

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PDE-based inpainting using corner information [Zimmer, 2007]

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- Interleaving mean curvature motion (MCM) and edge-enhancing diffusion (EED) for reconstruction

Previous Work

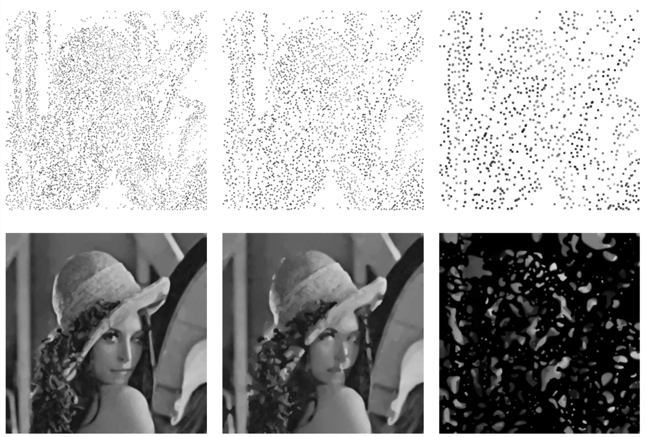

Figure 3: Reconstruction from corner regions of different sizes [Zimmer, 2007]

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- Pure EED inpainting

Corner Regions + Localisation

Corner Detection based on the Structure Tensor

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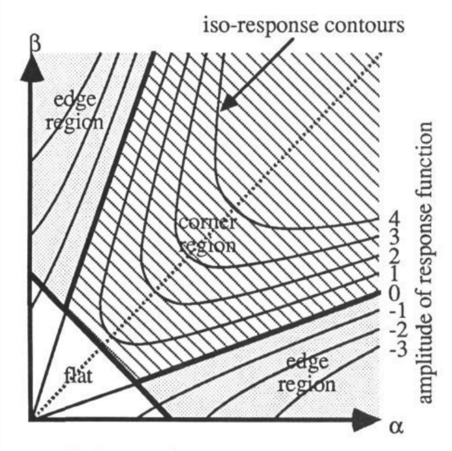

Figure 4: Visualization of relation between eigenvalues of structure tensor [Harris and Stephens, 1988]

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- Local maxima marked as corners

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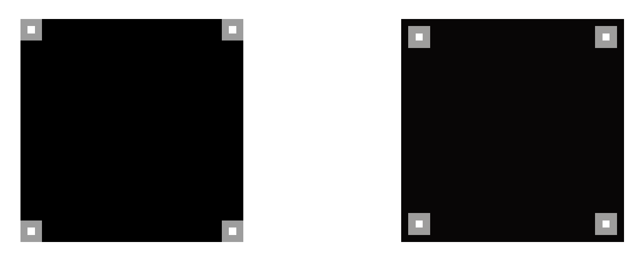

Figure 4: Corner regions similar to approach of [Zimmer, 2007] for different integration scales. **Left:** $\rho = 2$ **Right:** $\rho = 4$

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- Reconstruction errors

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- Detected position might not align with actual position
- Reconstruction errors
- Increasing integration scale to restrict amount of mask pixels not viable (as in [Zimmer, 2007])

Choosing the Mask Radius

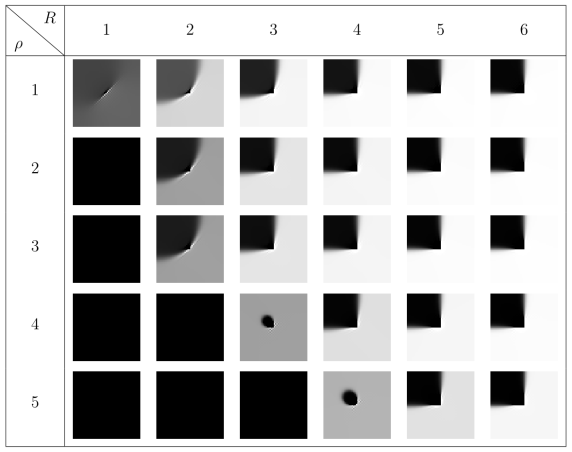

Figure 4: Matrix containing reconstruction results for different combinations of integration scale and mask radius

Choosing the Mask Radius

ρ \ R	1	2	3	4	5	6
1	**4.83**	**10.97**	15.70	20.39	22.71	23.58
2	1.25	7.89	**17.31**	**21.48**	**23.45**	24.13
3	1.25	7.89	**17.31**	**21.48**	**23.45**	24.13
4	1.25	1.25	7.21	16.91	22.92	**24.34**
5	1.25	1.25	1.25	7.84	17.96	22.82

Figure 5: PSNR Values for reconstructed images from previous slide

Choosing the Mask Radius

Results:

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Additional Modifications

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Amount of corners varying on input image with fixed threshold
Makes it hard to reliably produce masks of the same size

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Alternative

Instead of filtering out percentage of corners, calculate upper bound for number of corners such that only a certain percentage of *pixels* is kept.

Percentile Thresholding

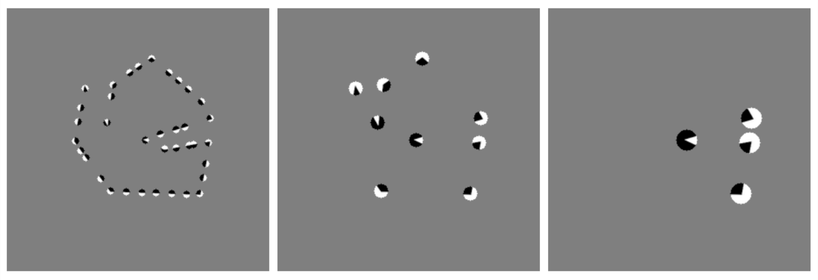

Figure 6: Mask of similar size for different radii. Upper bound: 2% of total pixels. Actual sizes: 1.95%, 1.97%, 1.96%

Non-maximum Suppression

Observation

Corner regions tend to overlap a lot, especially in textured regions

Results in poorly distributed inpainting mask

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Possible Remedy

Discard corners already covered by a ‘better’ corner

Non-maximum Suppression

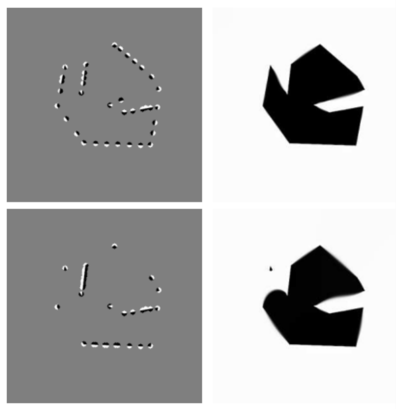

Figure 7: Effect of CNMS on the distribution of corner regions across the image. Parameters: $\sigma = 1, \rho = 1, R = 4, q = 0.02$. **Top:** CNMS, **Bottom:** no CNMS

Reconstruction

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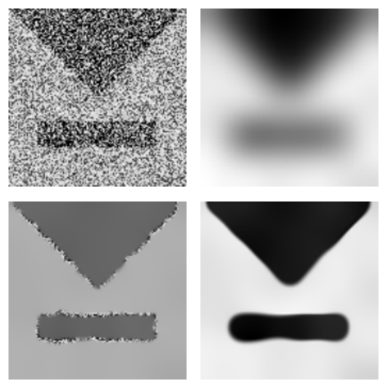

Figure 8: Top Left: Original image, **Top Right:** Homogeneous Diffusion, **Bottom Left:** Nonlinear isotropic diffusion, **Bottom Right:** EED

Reconstruction

- Reconstruction based on edge-enhancing diffusion
- Type of anisotropic diffusion governed by PDE

$$\partial_t u = \mathrm{div}(g(\nabla u_\sigma \nabla u_\sigma^\top)\nabla u)$$

- Originally meant for denoising
- Considered one of the best inpainting operators [Schmaltz et al., 2014]

Reconstruction

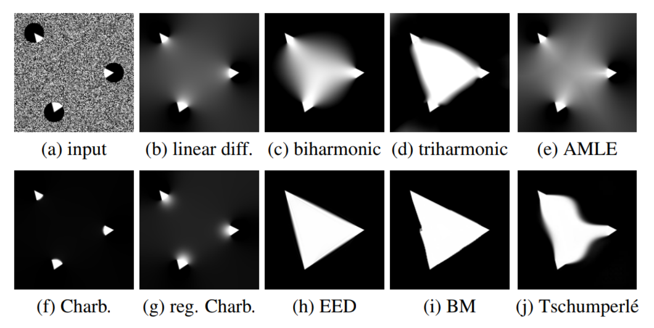

Figure 8: Comparison of inpainting operators [Schmaltz et al., 2014]

Results

Results

Figure 9: Left: Original image, **Middle:** Inpainting mask ($\sigma = 1, \rho = 1, R = 7, q = 0.02$) 1.99% of all pixels, **Right:** Reconstruction ($\sigma = 2, \lambda = 0.1, \alpha = 0.49, \gamma = 1, PSNR : 18.35$)

Results

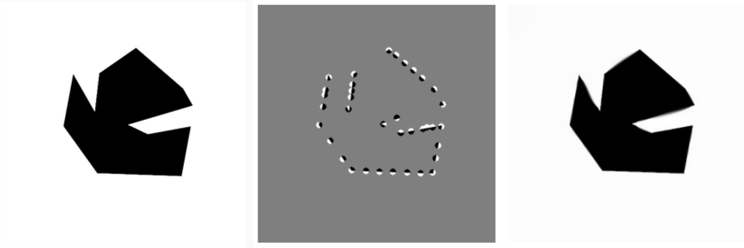

Figure 10: Left: Original image, **Middle:** Inpainting mask ($\sigma = 1, \rho = 1, R = 4, q = 0.02$) 1.96% of all pixels, **Right:** Reconstruction ($\sigma = 2, \lambda = 0.1, \alpha = 0.49, \gamma = 1, PSNR : 31.45$)

Results

Figure 11: Left: Original image, **Middle:** Inpainting mask ($\sigma = 1, \rho = 1, R = 10$) 4.74% of all pixels, **Right:** Reconstruction ($\sigma = 2, \lambda = 0.2, \alpha = 0.49, \gamma = 1, PSNR : 18.35$)

Results

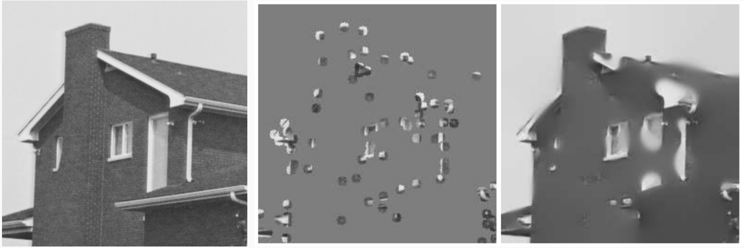

Figure 12: Left: Original image, **Middle:** Inpainting mask ($\sigma = 1, \rho = 1, R = 5, q = 0.1$) 9.23% of all pixels, **Right:** Reconstruction ($\sigma = 2, \lambda = 0.4, \alpha = 0.49, \gamma = 1, PSNR : 21.11$)

Figure 13: Left: Original image, **Middle:** Inpainting mask ($\sigma = 1.5, \rho = 2, R = 6, q = 0.02$) 1.88% of all pixels, **Right:** Reconstruction ($\sigma = 2, \lambda = 0.2, \alpha = 0.49, \gamma = 1, PSNR : 20.74$)

Results

Figure 14: Left: Original image, **Middle:** Inpainting mask ($\sigma = 1.5, \rho = 2, R = 6, q = 0.02$) 1.88% of all pixels, **Right:** Reconstruction ($\sigma = 2, \lambda = 0.2, \alpha = 0.49, \gamma = 1, PSNR : 16.25$)

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- Choose mask radius at least as large as integration scale
- Fairly good results for binary images
- Struggles with textured images
- Corners are fairly seldom

Any questions?

Thank you for your time!

References

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Appendix