Poisson Image Editing using Perona-Malik Diffusion

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Motivation

- Poisson Image Editing (Pérez et al., 2003) is a well-established method for seamlessly cloning regions from one image onto another. Given a source image S, a target image T, and a mask $\Omega \subseteq \mathbb{R}^2$, the blended image B is constructed to have diffusion guided by a vector field v inside Ω (typically ∇S), while matching the target on $\partial\Omega$ and outside Ω.
- This is achieved by solving the Poisson equation $\Delta B = \nabla \cdot v$ in Ω, with v typically ∇S, with $B = T$ on Ω and $\nabla B = \nabla T$ on $\partial\Omega$.
- Unfortunately, when cloning the source atop the target with $v = \nabla S$, the classical formulation of Poisson Image Editing neglects gradient information of T close to $\partial\Omega$, and diffuses across strong edges of T.
- There is thus a need for Poisson Image Editing that respects the edge structure of the target image close to the mask boundary.

Related Work

- Pérez et al. (2003) respect the edge information from T by modifying the guidance field v only when the source is transparent or has holes.
- Hua et al. (2014) addresses blurring across edges in standard Poisson blending by casting the PDE as a variational problem, to which they add edge-aware constraints. They do not, however, modify the diffusion operator, which can also be made edge-aware.
- Perona & Malik (1990) introduce a nonlinear diffusion operator for image denoising, acting on scalar fields f as $\nabla \cdot (c(x)\nabla f)$, where $c(x)$ is a spatially varying diffusion coefficient. Particularly, if $c(x)$ decays with gradient magnitude, the diffusion operator models smoothing while retaining edge structure.

References

[1] Pérez, Gangnet, & Blake, Poisson Image Editing, ACM Transactions on Graphics, 22(3), 313–318, 2003.
[2] Perona & Malik, Scale-space and edge detection using anisotropic diffusion, IEEE Transactions on Pattern Analysis and Machine Intelligence, 12(11), 1990.
[3] Hua, M., Bie, X., Zhang, M., & Wang, W. Edge-aware gradient domain optimization framework for image filtering by local propagation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2014.

Method

- We replace the Laplacian operator in the Poisson problem with the edge-aware Perona-Malik diffusion operator with fixed conductivities:

$$\nabla \cdot (c(x)\nabla B) = \nabla \cdot (c(x)v) \text{ in } \Omega$$

$$B = T \text{ on } \partial\Omega \text{ and outside } \Omega$$

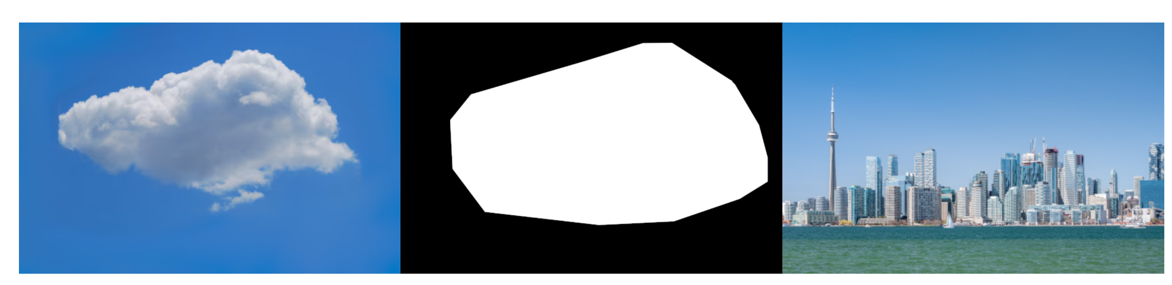
where $c(x)$ is the conductivity map given by

$$c(x) = \min\left(\frac{1}{1 + (|\nabla S|/\kappa)^2}, \quad \frac{1}{1 + (|\nabla T|/\kappa)^2}\right)$$

and κ is a sensitivity parameter. Thus, $c(x)$ is small near edges in both S and T.
- We discretize the problem on the image grid using a 5-point finite difference stencil, with $c(x)$ sampled at the inter-pixel edges.

Experimental Results

We measure the structural similarity index (SSIM) inside the masked region Ω against both the target (SSIM_T) and source (SSIM_S). Higher is better.



source mask target

$\kappa = 0.01$	$\kappa = 0.02$	$\kappa = 0.03$	PIE ($\kappa \to \infty$)
$\text{SSIM}_T = 0.69$	$\text{SSIM}_T = 0.68$	$\text{SSIM}_T = 0.67$	$\text{SSIM}_T = 0.63$
$\text{SSIM}_S = 0.71$	$\text{SSIM}_S = 0.72$	$\text{SSIM}_S = 0.74$	$\text{SSIM}_S = 0.76$

PIE ($\kappa \to \infty$)	$\kappa = 0.045$
$\text{SSIM}_T = 0.18$	$\text{SSIM}_T = 0.28$
$\text{SSIM}_S = 0.66$	$\text{SSIM}_S = 0.75$

PIE ($\kappa \to \infty$)	$\kappa = 0.03$
$\text{SSIM}_T = 0.49$	$\text{SSIM}_T = 0.53$
$\text{SSIM}_S = 0.92$	$\text{SSIM}_S = 0.95$