

Project Motivation and Goals:

Noise corrupts every image taken with a physical camera. Understanding and mitigating all types of noise is crucial for making accurate measurements in scientific as well as artistic applications alike. For my final project, I would like to characterize a noise model for a camera that I have (as many noise sources as relevant or possible). I would also like to implement a denoising algorithm using ADMM as well as come up with my own regularizer for it. As a potential extension (time permitting), I would like my regularizer to be designed based on the noise model developed during camera calibration.

Timeline:

2/19 - Collect dark and light images to characterize Fixed Pattern Noise

2/26 - Measure noise at different intensities to validate shot noise model, develop full model based on

$$SNR = \frac{\text{mean pixel value}}{\text{standard deviation of pixel value}} = \frac{\mu \leftarrow \text{signal}}{\sigma \leftarrow \text{noise}}$$

$$= \frac{PQ_e t}{\sqrt{PQ_e t + Dt + N_r^2}}$$

— signal-dependent
— signal-independent

3/5 - Implement ADMM & purpose it for a poisson noise model

Algorithm ADMM

1. Set $k = 0$, choose $\mu > 0$, $\mathbf{u}_0$, and $\mathbf{d}_0$.
2. **repeat**
3. $\mathbf{z}_{k+1} \in \arg \min_{\mathbf{z}} f_1(\mathbf{z}) + \frac{\mu}{2} \|\mathbf{G} \mathbf{z} - \mathbf{u}_k - \mathbf{d}_k\|_2^2$
4. $\mathbf{u}_{k+1} \in \arg \min_{\mathbf{u}} f_2(\mathbf{u}) + \frac{\mu}{2} \|\mathbf{G} \mathbf{z}_{k+1} - \mathbf{u} - \mathbf{d}_k\|_2^2$
5. $\mathbf{d}_{k+1} \leftarrow \mathbf{d}_k - (\mathbf{G} \mathbf{z}_{k+1} - \mathbf{u}_{k+1})$
6. $k \leftarrow k + 1$
7. **until** stopping criterion is satisfied.

Algorithm Poisson Image Deconvolution by AL (PIDAL-TV)

1. Choose $\mathbf{u}_0^{(1)}, \mathbf{u}_0^{(2)}, \mathbf{u}_0^{(3)}, \mathbf{d}_0^{(1)}, \mathbf{d}_0^{(2)}, \mathbf{d}_0^{(3)}, \mu$, and τ . Set $k \leftarrow 0$.
2. **repeat**
3. $\boldsymbol{\zeta}_k^{(1)} \leftarrow \mathbf{u}_k^{(1)} + \mathbf{d}_k^{(1)}$
4. $\boldsymbol{\zeta}_k^{(2)} \leftarrow \mathbf{u}_k^{(2)} + \mathbf{d}_k^{(2)}$
5. $\boldsymbol{\zeta}_k^{(3)} \leftarrow \mathbf{u}_k^{(3)} + \mathbf{d}_k^{(3)}$
6. $\boldsymbol{\gamma}_k \leftarrow \mathbf{K}^T \boldsymbol{\zeta}_k^{(1)} + \boldsymbol{\zeta}_k^{(2)} + \boldsymbol{\zeta}_k^{(3)}$
7. $\mathbf{z}_{k+1} \leftarrow (\mathbf{K}^T \mathbf{K} + 2\mathbf{I})^{-1} \boldsymbol{\gamma}_k$
8. $\boldsymbol{\nu}_k^{(1)} \leftarrow \mathbf{K} \mathbf{z}_{k+1} - \mathbf{d}_k^{(1)}$
9. $\mathbf{u}_{k+1}^{(1)} \leftarrow \arg \min_{\mathbf{v}} \frac{\mu}{2} \|\mathbf{v} - \boldsymbol{\nu}_k^{(1)}\|_2^2 + \sum_{i=1}^m \xi(v_i, y_i)$
10. $\boldsymbol{\nu}_k^{(2)} \leftarrow \mathbf{z}_{k+1} - \mathbf{d}_k^{(2)}$
11. $\mathbf{u}_{k+1}^{(2)} \leftarrow \arg \min_{\mathbf{v}} \frac{\mu}{2} \|\mathbf{v} - \boldsymbol{\nu}_k^{(2)}\|^2 + \tau \text{TV}(\mathbf{v})$.
12. $\boldsymbol{\nu}_k^{(3)} \leftarrow \mathbf{z}_{k+1} - \mathbf{d}_k^{(3)}$
13. $\mathbf{u}_{k+1}^{(3)} \leftarrow \arg \min_{\mathbf{v}} \frac{\mu}{2} \|\mathbf{v} - \boldsymbol{\nu}_k^{(3)}\|^2 + \iota_{\mathbb{R}_+^n}(\mathbf{v})$.
14. $\mathbf{d}_{k+1}^{(1)} \leftarrow \mathbf{d}_k^{(1)} - (\mathbf{K} \mathbf{z}_{k+1} - \mathbf{u}_{k+1}^{(1)})$
15. $\mathbf{d}_{k+1}^{(2)} \leftarrow \mathbf{d}_k^{(2)} - (\mathbf{z}_{k+1} - \mathbf{u}_{k+1}^{(2)})$
16. $\mathbf{d}_{k+1}^{(3)} \leftarrow \mathbf{d}_k^{(3)} - (\mathbf{z}_{k+1} - \mathbf{u}_{k+1}^{(3)})$
17. $k \leftarrow k + 1$
18. **until** some stopping criterion is satisfied.

3/12 - Create a prior and integrate it into ADMM algorithm

3/13 - Final Poster due

Related work and scientific references:

In “Restoration of Poissonian Images Using Alternating Direction Optimization”, Mario Figueiredo and Jose Bioucas-Dias study ADMM and under which conditions convergence can be achieved. They implement the algorithm to deconvolving Poissonian noise found in images.

In “<http://www.hpl.hp.com/techreports/2008/HPL-2008-159.pdf>”, SukHwan Lim study how to extract noise parameters from images without knowledge of the imaging pipeline.

In “Practical Poissonian-Gaussian noise modeling and fitting for single-image raw-data”, Alessandro Foi, Mejdi Trimeche, Vladimir Katkovnik, and Karen Egiazarian develop a noise model for the raw-data of digital image sensors. They also illustrate how to estimate the noise parameters of their model from a single noisy image.