Compressed Low-Light Scene Reconstruction using Hyper-spectral Single Photon Lidar

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Objectives

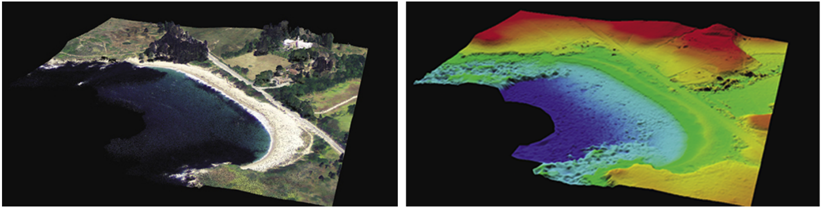
- LiDAR data $\rightarrow$ 2D Image $+$ Depth
- **Goal** $\rightarrow$
  - Reconstruct 2D intensity images at multiple wavelengths
  - Under low-light (limited observed data) conditions
  - From incomplete data

Outline

Outline

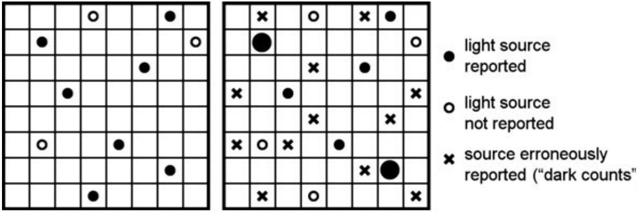
Introduction

- Can detect a single photon reflected from the target
- Operate at multiple wavelengths from IR to Visible
- Collects data in a raster scanning fashion



source: NASA

Why is this work important?

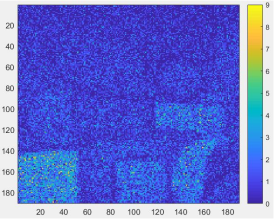


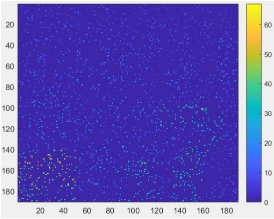
source: Single-Photon Imaging[1]

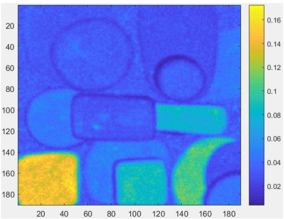
- Left : Photons interacting with the sensor
- Right : Photon detection process
- Low-intensity photons sparsely distributed → impossible to differentiate from dark counts

[1] Seitz, Peter, and Albert JP Theuwissen, eds. Single-photon imaging. Vol. 160. Springer Science & Business Media, 2011.

Problem Definition







- Left : Photons collected uniformly at all pixels
- Center : More photons collected randomly at $\sim$ 6% pixels
- Right : Ground truth intensity image

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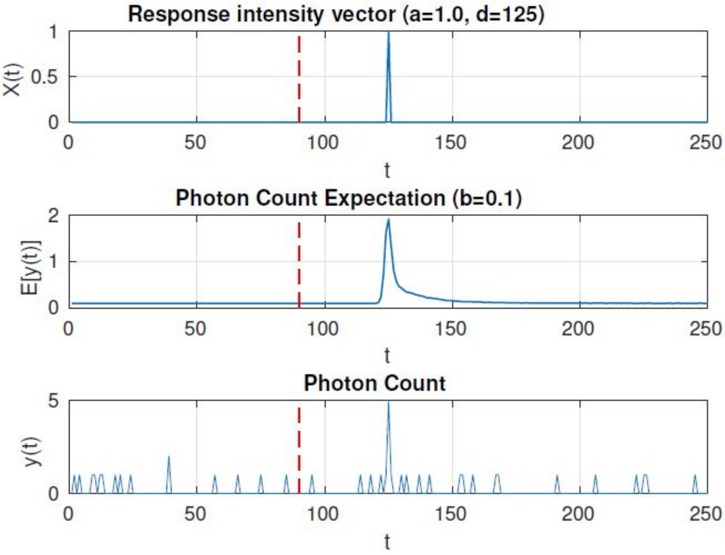
Observation Model



Observation Model (contd . . .)

- Baseline intensity (at pixel p and wavelength l):

$$y_{p,l} \sim Pr(b_{p,l}) \tag{1}$$

- Response Intensity :

$$y_{p,l} \sim Pr(r_{p,l} F_l a_{p,l} + b_{p,l}) \tag{2}$$

- where,
  - $y_{p,l} \rightarrow$ photon counts summed over t_b/t_a
  - $Pr(\lambda) \rightarrow$ Poisson distribution with mean intensity λ
  - $b \rightarrow$ baseline intensity, $a \rightarrow$ response intensity
  - $r_{p,l} \rightarrow$ vignetting effect, $F_l \rightarrow$ calibration data
- Minimize negative log-likelihood :

$$\mathcal{L}_{Y,\alpha}(A|\hat{B}) = \sum_{l=1}^{L} \sum_{p \in S_{\alpha,l}} [-\log(Pr(\lambda))] \tag{3}$$

- where, $S_{\alpha,l}$ represents a set of randomly selected pixels

Outline

Regularization - TV and NN

- Total Variation (TV)
  - Integral of the absolute gradient
  - Promotes spatial correlation & sparsity
  - Spectral TV -

$$STV(X) = \sum_{l=1}^{L} TV(x_l) \tag{4}$$

- Nuclear Norm (NN)
  - Consider $X \in \mathbb{R}^{N \times L}$, $N \rightarrow$pixels, $L \rightarrow$wavelengths
  - Sum of absolute singular values of X
  - $||X||_*$, where, $X = U\Sigma V^T$ is the SVD decomposition

Minimization Problem - TVNN

- Given by[2],

$$\hat{X} = \arg\min_{X}[\mathcal{L}_{Y,\alpha}(X) + \tau_1 STV(X) + \tau_2 ||X||_* + i_{\mathbb{R}^+}(X)] \quad (5)$$

- $i_{\mathbb{R}^+}(X)$ is indicator function enforcing positivity
- Computing SVD can be slow
- Requires manual tuning of two parameters

[2] Thanks to Rodrigo Daudt (student of Vibot#10)

Regularization - Joint Sparsity

- Joint Sparsity or group TV regularization
- ℓ_2 norm on the rows $\rightarrow$ promotes spectral correlation
- followed by ℓ_1 norm $\rightarrow$ promotes smoothness or spatial correlation
- Promotes joint sparsity and low-rankness
- Represented by

$$\hat{X} = \arg\min_{X} \left[\mathcal{L}_{Y,\alpha}(X) + \tau_1 ||\Psi^{\dagger} X||_{2,1} + i_{\mathbb{R}^+}(X) \right] \tag{6}$$

- where, Ψ is any wavelet basis in which data is sparse
- Much faster than the TVNN model

Algorithmic Details

- Alternating Direction Method of Multipliers (ADMM) algorithm
- Fast - usually converges within tens of iterations
- Guaranteed convergence
- Initialization does not need to be specific

Outline

Results

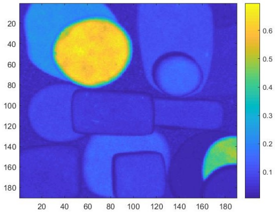
$$SNR = 10 \log \left(\frac{||\hat{x}||_2^2}{||\hat{x} - x||_2^2} \right) \tag{7}$$

before subsampling	sub-sampling ratio	after sub-sampling
0.5, 1, 2, 4, 8	1, 1/2, 1/4, 1/8, 1/16	0.5
1, 2, 4, 8, 16	1, 1/2, 1/4, 1/8, 1/16	1
10, 20, 40, 80, 160	1, 1/2, 1/4, 1/8, 1/16	10
50, 100, 200	1, 1/2, 1/4	50
100, 200	1, 1/2	100

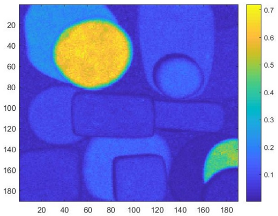
Results - Qualitative

ppp \ α		1	1/2	1/4	1/8	1/16
50	TVNN	46.74	<u>48.69</u>	46.33		
	JS-DCT	<u>47.95</u>	47.27	42.68		
	JS-DWT	<u>**48.99**</u>	47.97	43.79		
10	TVNN	34.38	41.33	<u>42.79</u>	39.75	35.69
	JS-DCT	37.58	<u>42.12</u>	40.22	36.03	31.69
	JS-DWT	39.29	<u>**43.14**</u>	41.43	37.34	27.83
1	TVNN	22.65	27.77	34.42	<u>**35.89**</u>	32.73
	JS-DCT	28.25	30.64	<u>31.06</u>	30.34	28.01
	JS-DWT	27.22	27.31	<u>27.41</u>	27.15	21.87
0.5	TVNN	20.91	21.32	22.33	22.53	<u>23.09</u>
	JS-DCT	26.68	<u>26.95</u>	26.89	26.78	26.16
	JS-DWT	26.70	28.75	<u>**29.67**</u>	28.99	24.64

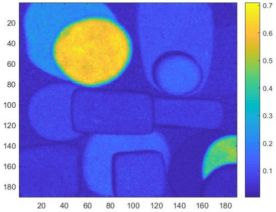
Results - Visual



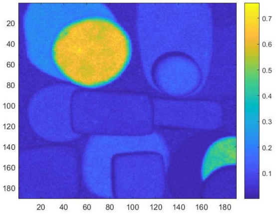
(a) Ground truth



(b) TVNN method

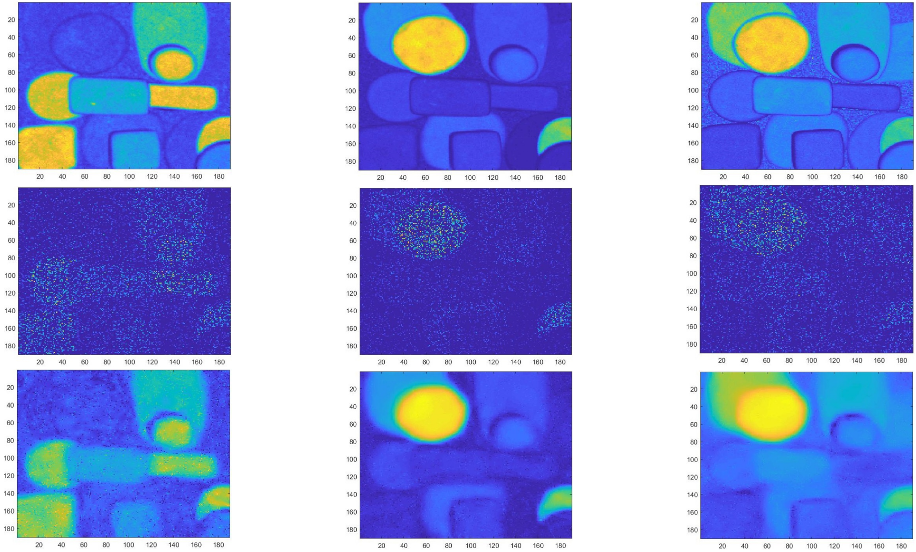


(c) JS-DWT method



(d) JS-DCT method

Results - Visual



Outline

Conclusion

- In-painting method with Poisson noise model
- Image intensity estimation in two sequential steps
- Two separate minimization problems proposed
- Good reconstructions from data with ~ 0.5 photons per pixel
- Improvement through compressed sensing

Limitations and Future Work

- **Limitations :**
  - First one month spent on a multi-scale approach
  - Testing TVNN consumed too much time
- **Future Work :**
  - Depth Estimation
  - Material classification
  - Improve Joint Sparsity method

Thank you for your attention!