Poisson Denoising with Dictionary Learning

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Guide

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Section-0
Previous Work

Previous work has been done by Pratham Desai and Amal Dani of CSE, IIT Bombay Class of 2016. The report for the same can be found over here:

https://docs.google.com/document/d/1Tbm3y4cvQrsOyv5btolSxWESVPCTkZXiZzb37Wa5XgM/edit?usp=sharing

https://drive.google.com/open?id=0B9dtCXaLvkHXU3ZrMkI2aEtOWEU

There have been changes we have proposed and incorporated over the work/code base provided by the above two. The improvements have caused the reconstruction to get better in both the cases of Gaussian and Poisson model, but Poisson model was able to generate better results than Gaussian overcoming the problem what the earlier duo have faced. Images used are standard Normalized Brodatz.

All the notations have been imported from their work, refer to their definitions in case of conflict.

Section-1
Mathematical formulation

Objectives and likelihoods:

Poisson Model:

Dictionary Learning:

$$ObjectiveFunction(D, \alpha) = \left(\sum_{i=1}^{n} [y_i \log (D\alpha)_i - (D\alpha)_i] - \lambda_{sparsity} \sum_{j=1}^{n} |\alpha_j| - \lambda_{reg} \sum_{l=1}^{k} \sum_{j \in C} V_j(D_l)\right)$$

Maximise the objective function while learning Dictionary **D,** and Coefficient matrix α.

Improvement:

Previously the potential function was Huber loss over 4 immediate neighbours. It has been changed to a **5*5** Gaussian Neighbourhood/Window with zero mean and standard deviation being **1.** This lead to better dictionaries as a whole given the MRF neighbourhood has increased its size.

Reconstruction:

$$\alpha^* = argmax_{\alpha} \left(\sum_{i=1}^{n} [y_i \log (D\alpha)_i - (D\alpha)_i] - \lambda_{sparsity} \sum_{j=1}^{n} \alpha_j \right)$$

As we have the dictionary already learnt and shall be using the same for image reconstruction. This will help us learn the coefficients required for the reconstruction.

Gaussian Model:

Dictionary Learning:

$$ObjectiveGaussian(D, \alpha) = \left(\sum_{j=1}^{n} ((D\alpha)_i - y_i)^2 + \lambda_{sparsity} \sum_{j=1}^{n} |\alpha_j| + \lambda_{reg} \sum_{l=1}^{k} \sum_{j \in C} V_j(D_l) \right)$$

Maximise the objective function while learning Dictionary **D,** and Coefficient matrix α.

Improvement:

Previously the potential function was Huber loss over 4 immediate neighbours. It has been changed to a **5*5** Gaussian Neighbourhood/Window with zero mean and standard deviation being **1**. This lead to better dictionaries as a whole given the MRF neighbourhood has increased its size.

Reconstruction:

$$\alpha^* = argmin_{\,\alpha} \left(\sum_{j=1}^{n} ((D\alpha)_i - y_i)^2 + \lambda_{sparsity} \sum_{j=1}^{n} \alpha_j \right)$$

As we have the dictionary already learnt and shall be using the same for image reconstruction. This will help us learn the coefficients required for the reconstruction.

Improvements done theoretically:

Entire Poisson model reconstruction was recoded leaving the previous one as the previous one was producing really bad reconstruction.

The initial choice of coefficients while reconstruction was random in the previous work which made the reconstruction non-deterministic due to various local minima/maxima attained in both the cases(Projected gradient descent or ascent). The initial choice now is the coefficient matrix obtained when we solve Least squares fit for $D\alpha = y$, y is the noisy image which we are denoising. And NNSC implies a constrained $\alpha >= 0$. Thus the obtained coefficients are used as initial coefficients and then are learnt from there onwards

Section-2
MATLAB Code - Structure and Guidelines

There are 2 platforms for the code:

1) Regularity_Gaussian
2) Regularity_Poisson

Regularity_Gaussian is the gaussian framework for Poisson denoising
Regularity_Poisson is the poisson framework for Poisson denoising

Regularity_Gaussian:

noisyImages.m - generates required Noisy images of required scale
testing_regularity_on_clean_images.m - generates dictionaries
testing_gd_on_image.m - reconstructs the required image given the dictionary

Regularity_Poisson:

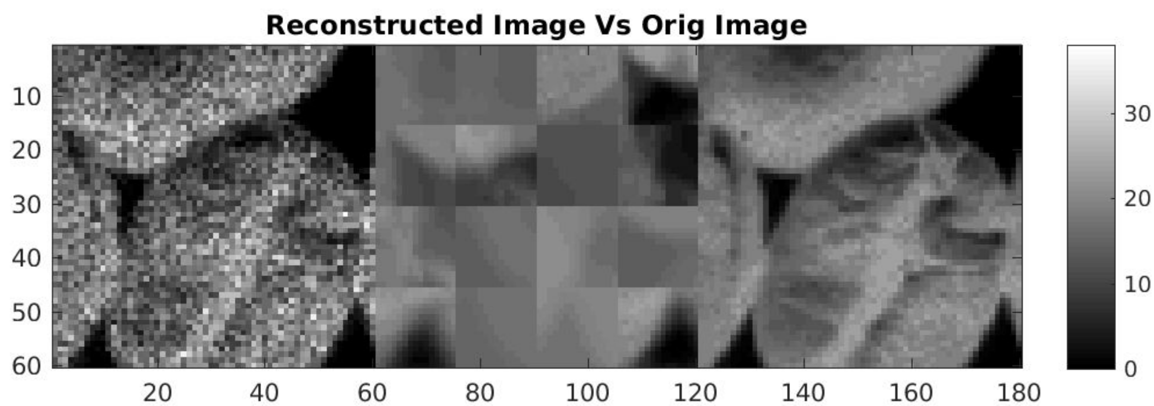
noisyImages.m - generates required Noisy images of required scale
ScriptToGenerateDictionaries.m - generates dictionaries
testing_poisson_on_image.m - reconstructs the required image given the dictionary

Rest are dependent functions and tweaking is easy given documentation in previous work.

Section-3
Experiments and Results

The previous reconstruction using Poisson model was not at all good even though gaussian was faring well. All image sizes are 256*256

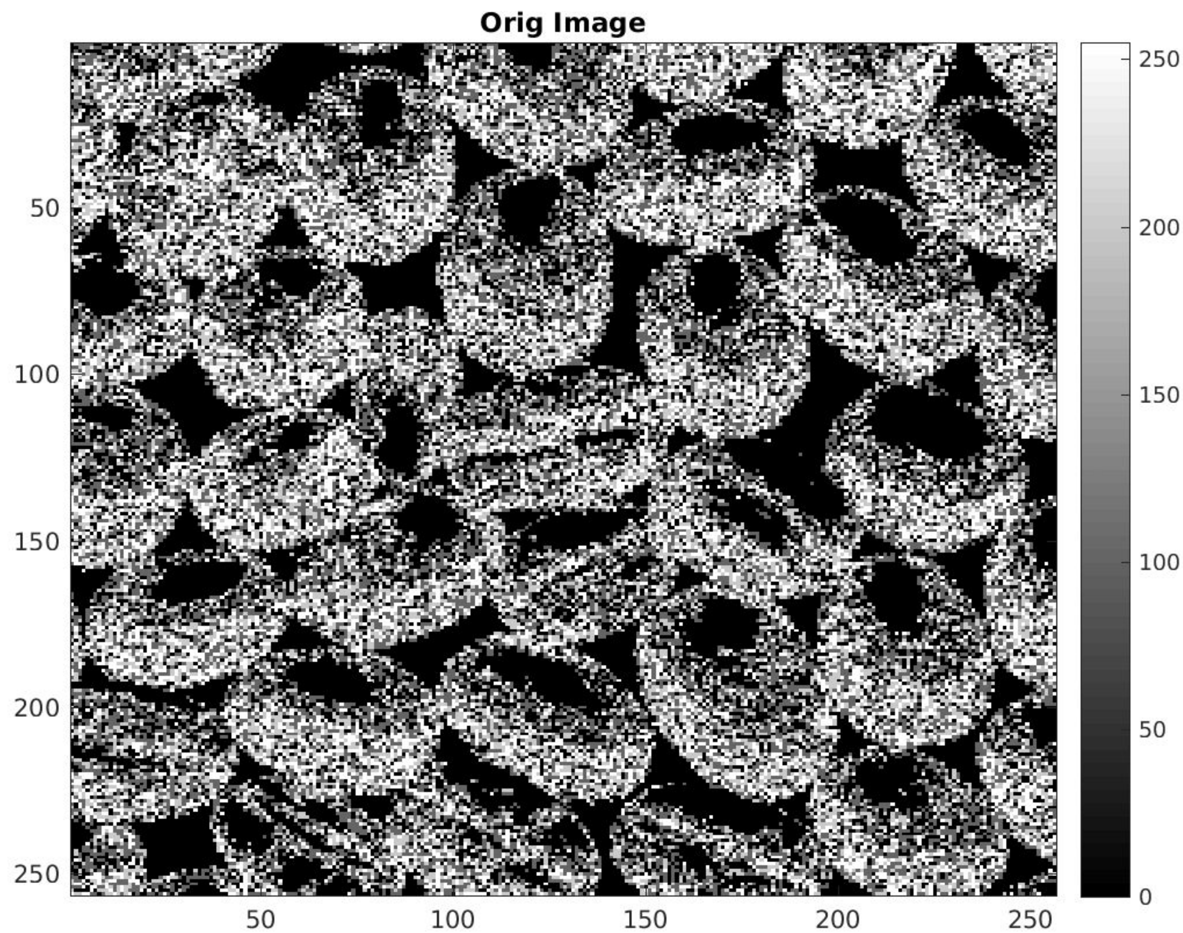
Previous Poisson reconstruction - Pratham & Amal:



This was due to some flaw in reconstruction code. The reconstruction code has been re-written with the changes in theory proposed above. The results are as follows for coffee bean image rest can be simulated.

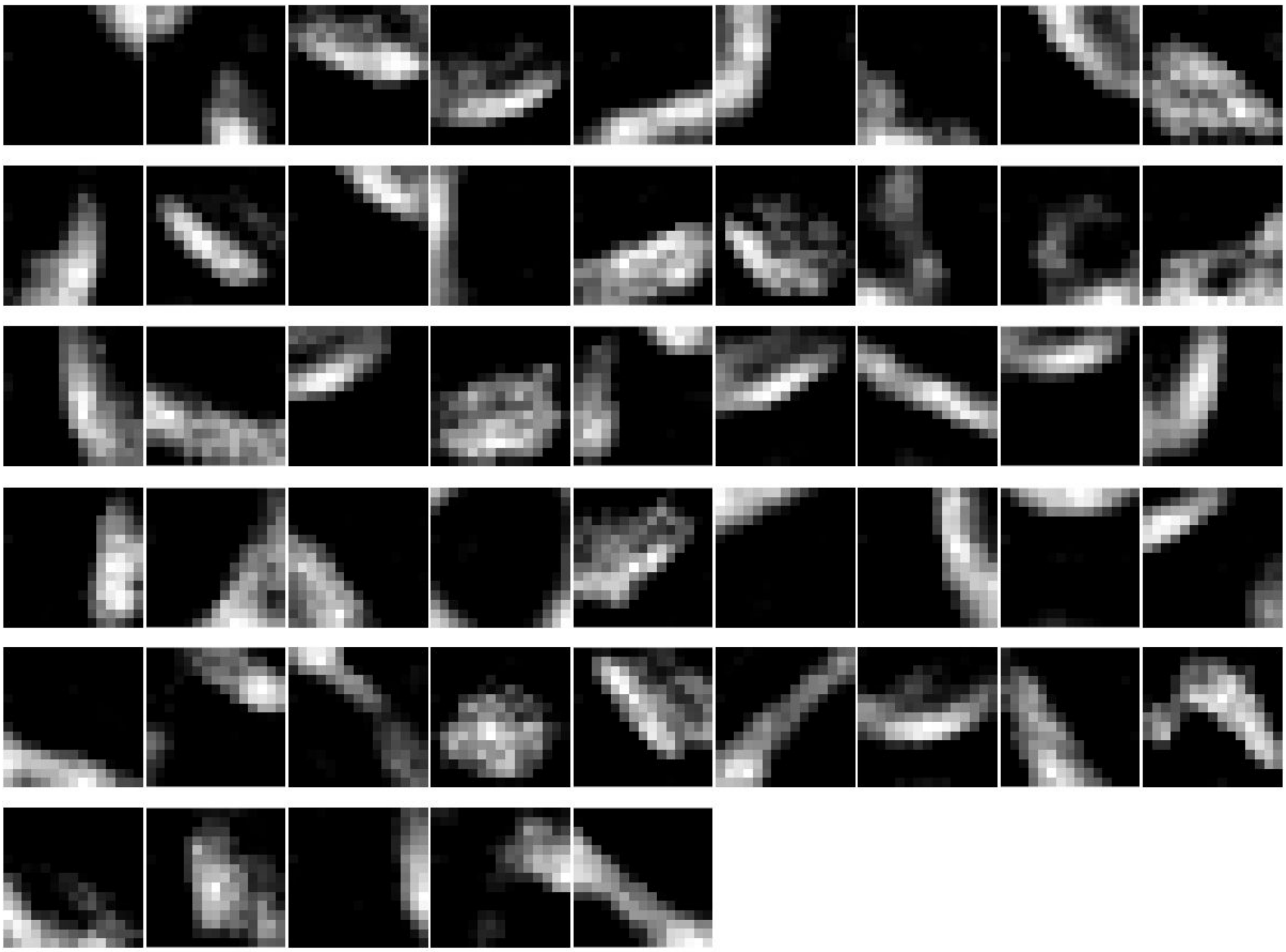
Noise Level: 100
Image: 74 (Coffee beans)

Noisy Image:

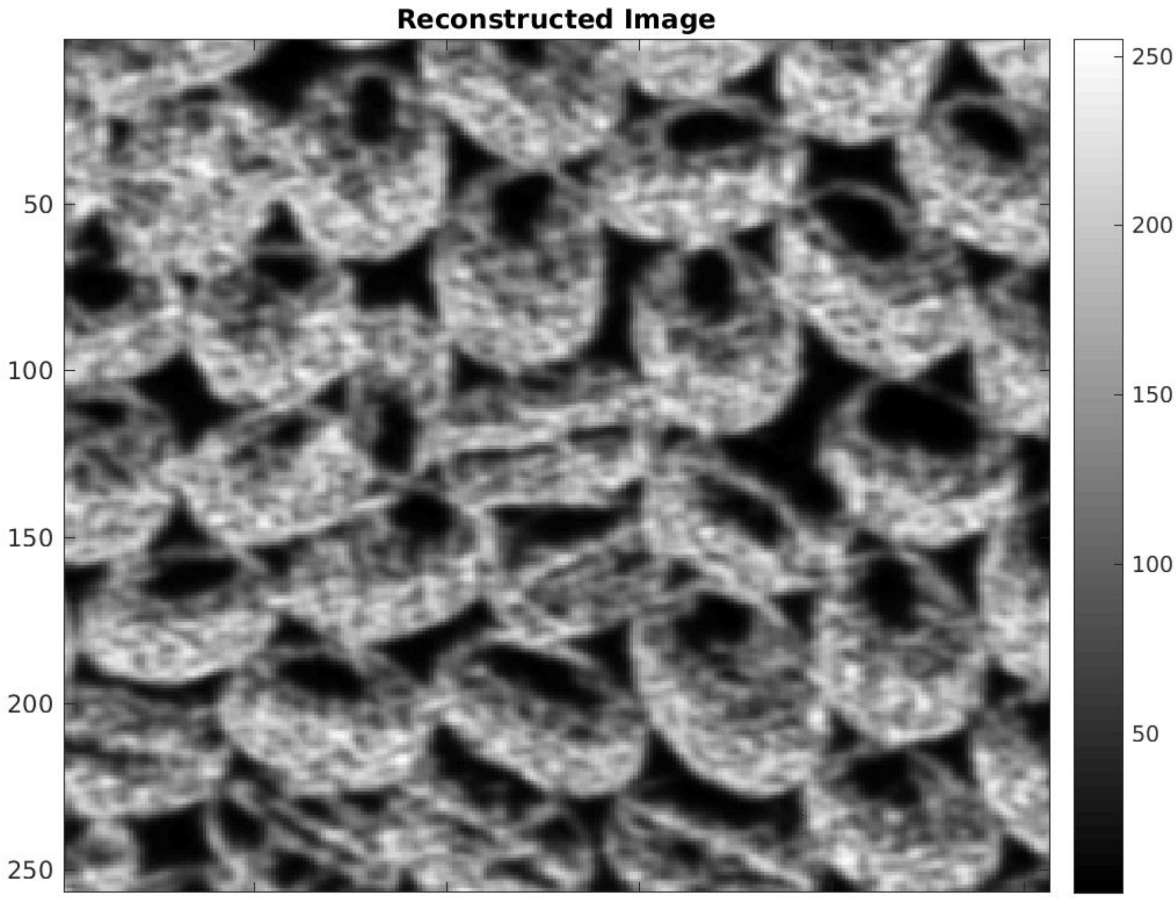


Gaussian Model:

Dictionary:

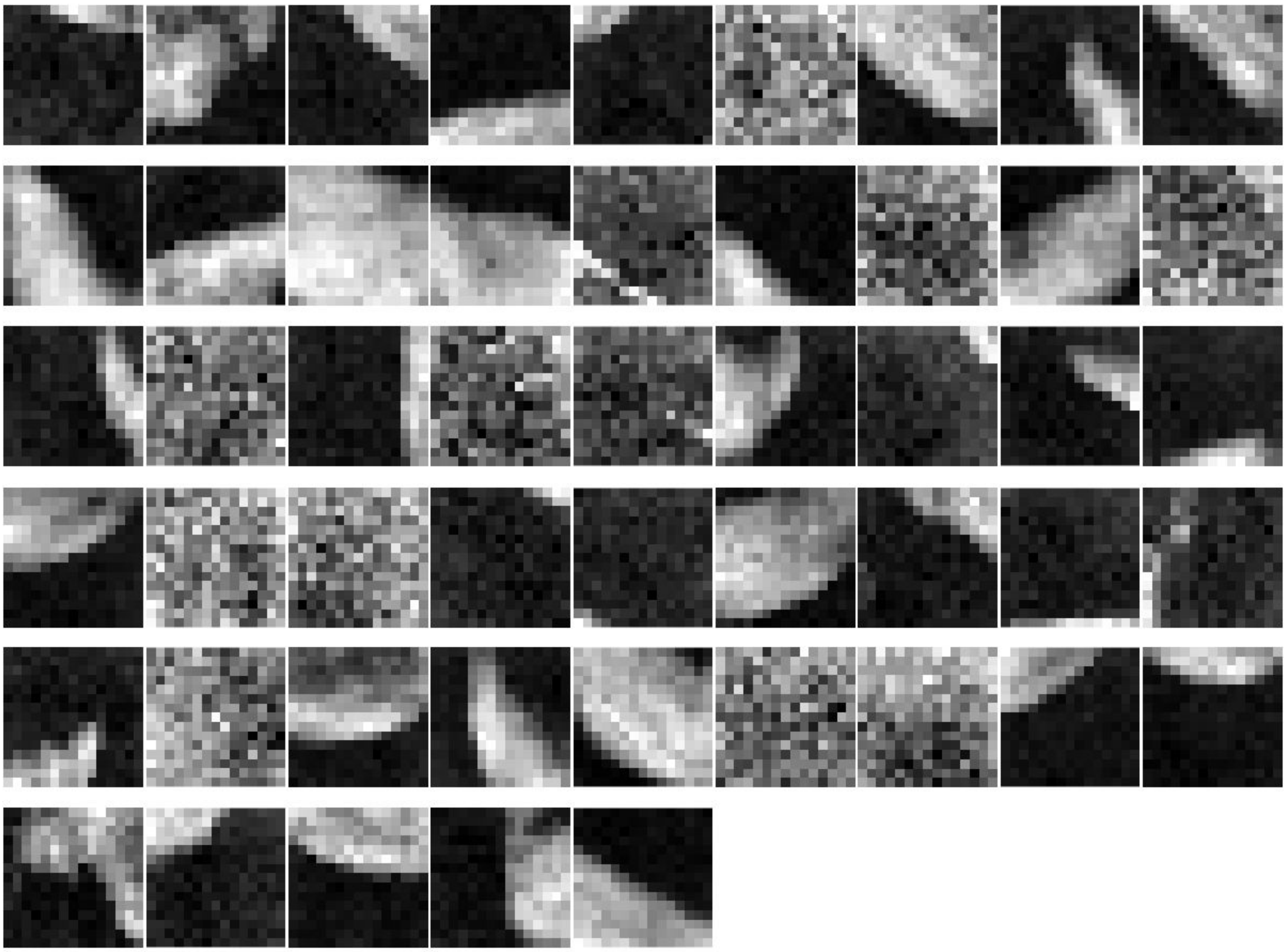


Reconstruction:

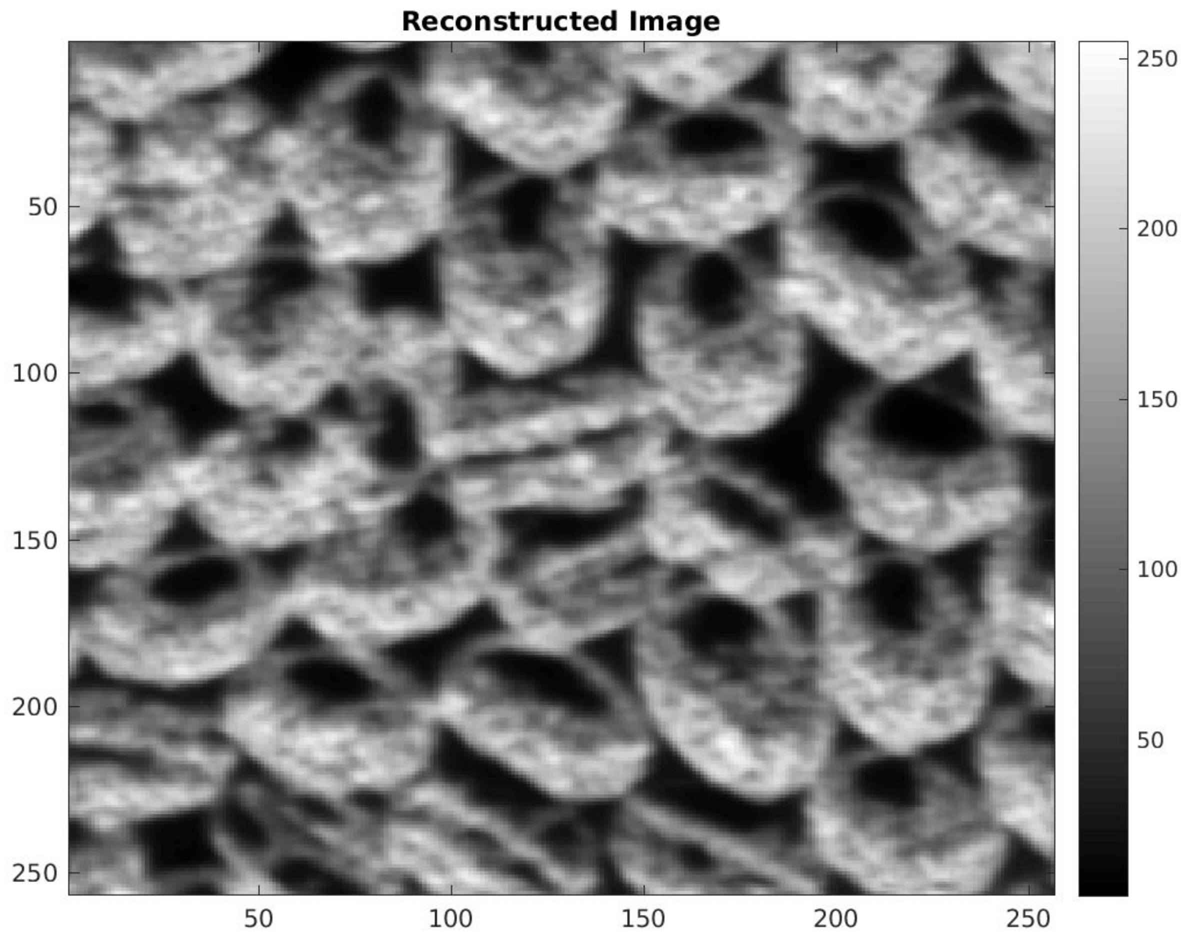


Poisson Model:

Dictionary:



Reconstruction:



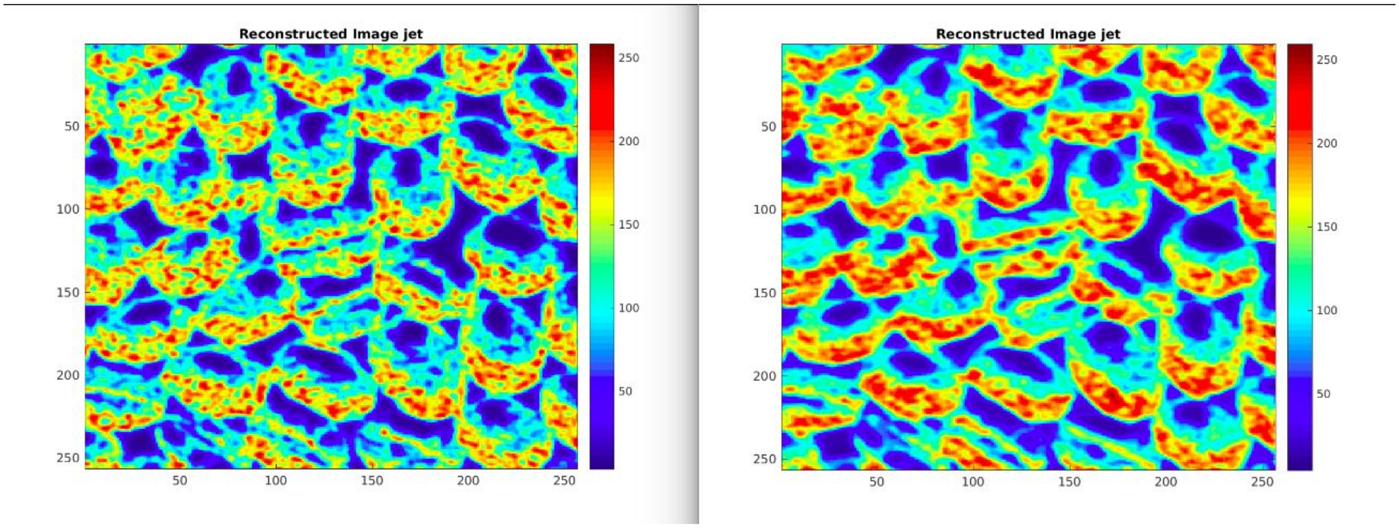
Rest of the results can be generated by running code.

Collection of results for various images: image numbers are from brodatz data

https://docs.google.com/spreadsheets/d/1gAURqXotmGNQ4cEGc-xSnYPfndH4xMpfZ26ODd_fJb8/edit?usp=sharing

This include 6 images at 4 different noise levels.

Image to show jet color map to prove the contrast factor

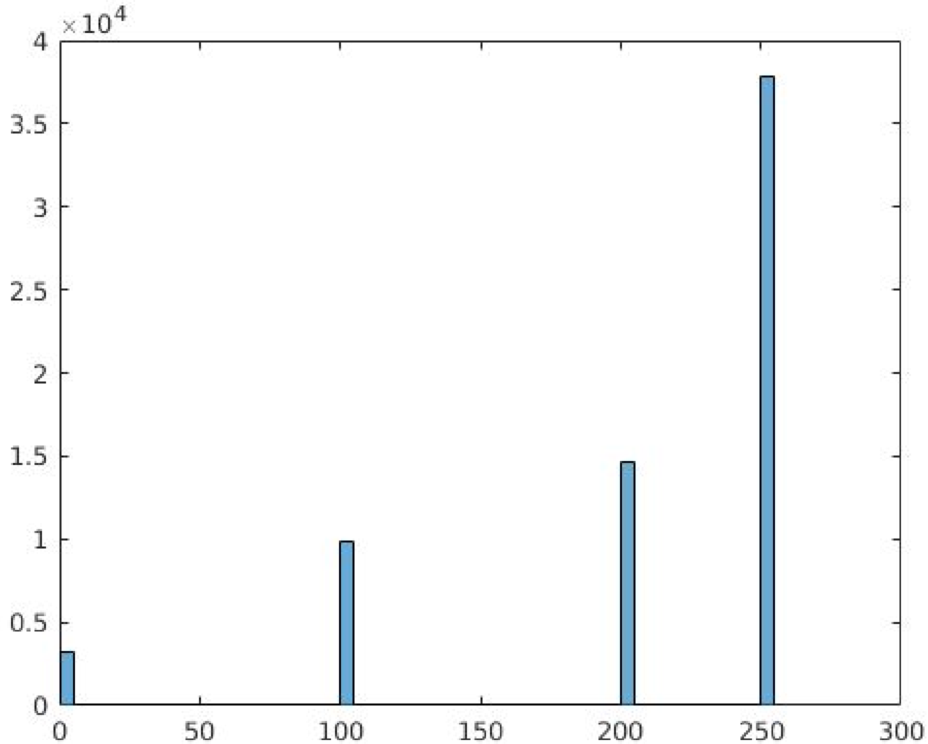


Left is gaussian model, right is poisson model

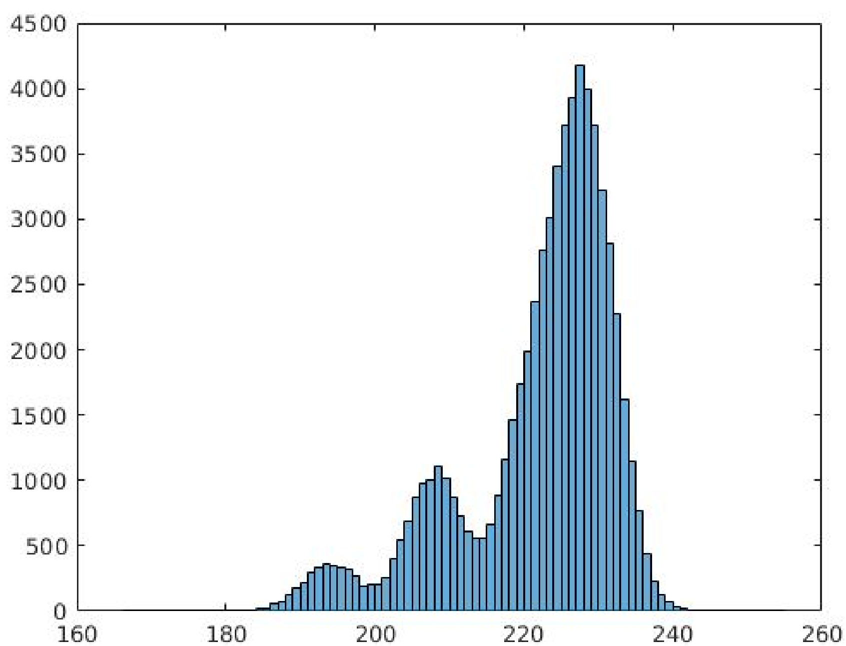
Experiment to show that lower values are lower in poisson when compared to gaussian, this helps to prove poisson gets better contrast during reconstruction

For a Plain image when added with noise:

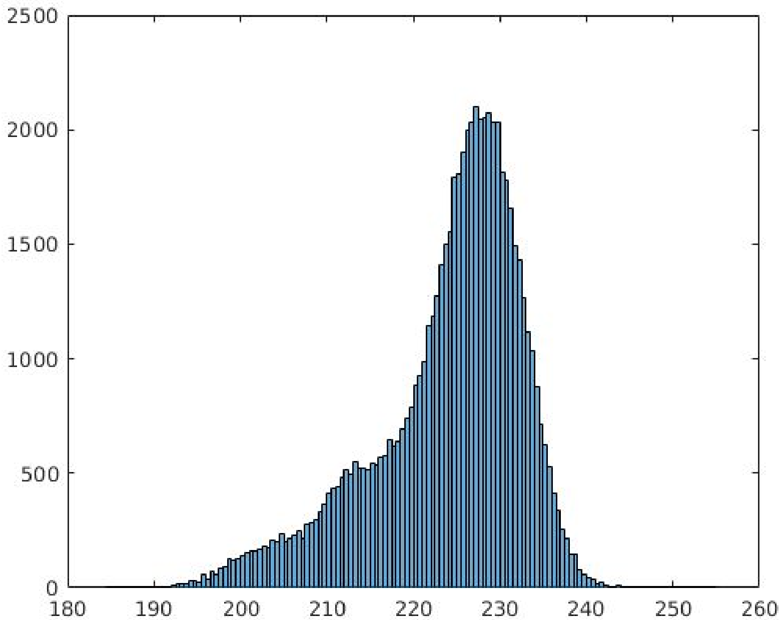
Noisy Image:



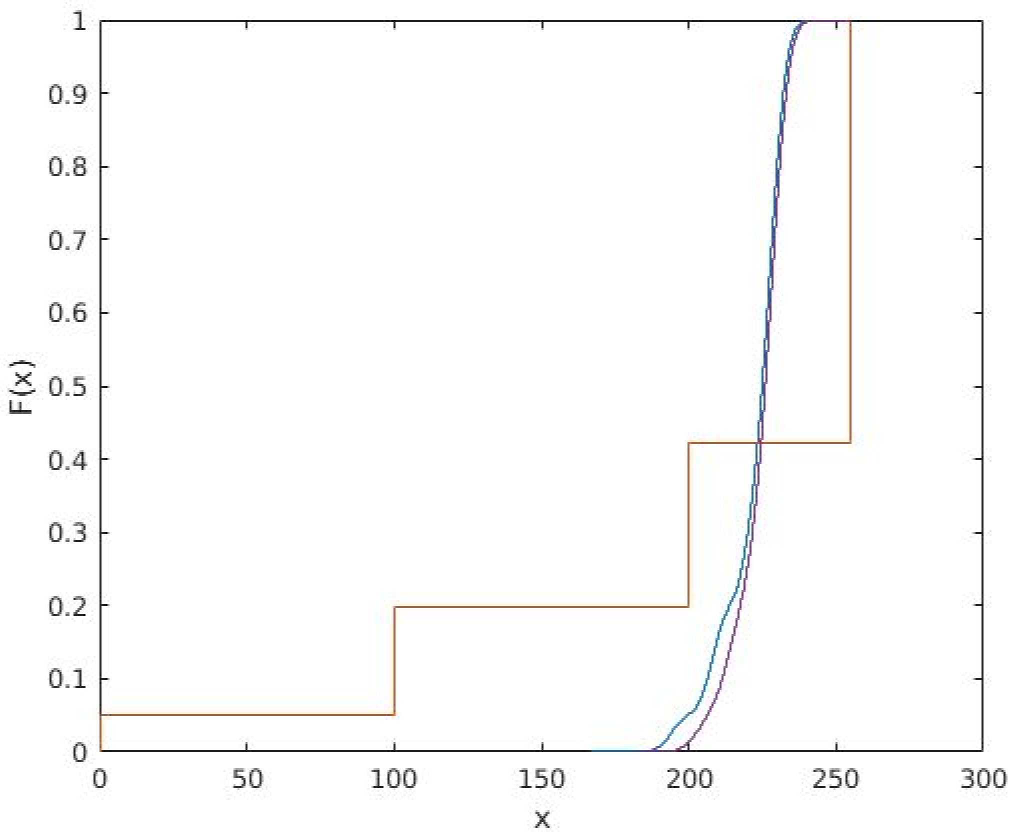
Poisson reconstruction:



Gaussian Reconstruction:



The cdfs of all three in the same image: Blue: Poisson, Purple: Gaussian, Orange: Noisy



Section-4

Conclusions and Future Work

Smoothness prior has no significant effect on the reconstruction and dictionaries learnt on images with poisson noise. Smoothness prior works efficiently only when there exist outliers (Read salt and pepper noise).

NNSC stands tall in the scene of chaos and is still valid and viable choice for the learning and reconstruction we have proposed

Poisson model out performs gaussian in most of the cases and significantly at higher noise levels (noise scale). It is on an average 10% better than gaussian reconstruction.

Poisson model shows significant betterment in cases of textured images (74, 75, 101) when compared to non textured images (23, 45).

Poisson model generates slightly better contrast compared to gaussian which can be seen in jet map images and stand alone experiment used to prove this. The cdf plot clearly shows the same along with histograms asserting it.

Blur in case of poisson reconstruction is significantly removed owing to the choice of MRF neighbourhood and initial choice of coefficients instead of random choice.

There are untapped territories regarding better choice of patches in order to save features (instead of naive high variance choice). Better prior information as smoothness seems to be ineffective.

Codebase:
https://www.dropbox.com/sh/be4oknqxjlch3cz/AAASi2GIG3VjmISgp7y3y8Wia?dl=0

https://drive.google.com/open?id=0B9dtCXaLvkHXUllnS2NpYUwwN3c

Section-5
References and Important Links

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1. Non Negative Sparse Coding by P. Hoyer.
   http://arxiv.org/pdf/cs/0202009.pdf

2. Sparsity Based Poisson Denoising with Dictionary Learning
   http://arxiv.org/pdf/1309.4306v3.pdf

3. For understanding image priors:
   https://www.cse.iitb.ac.in/~suyash/cs736/Slides_AlgoMIP_ImagePrior.pdf

4. Brodatz Images:
   http://multibandtexture.recherche.usherbrooke.ca/normalized_brodatz.html