# Evaluation of ADMM-based Poisson denoiser with different image priors on real experimental images

## Motivation

In many photon-limited imaging systems, such as photon counting and fluorescence microscopy, Poisson noise is usually the dominate type of noise in the image. Unlike other noises such as thermal noise or read noise which can be greatly reduced via hardware engineering efforts, Poisson noise results from the quantum nature of light and thus always exists in images under low light conditions. Therefore, denoising Poissonian images necessitates post-processing algorithms, many of which use image priors as regularizes when solving the inverse problem. Although many different image priors have been proposed for image denoising, existing papers working with Poisson noise usually simulate the noise on clean natural images and evaluate the denoisers on the synthetic data. Thus, it would be interesting to evaluate how the denoisers with different image priors/regularizes perform on real experimental Poissonian images with distinct features.

## Related works

A great variety of image priors/regularizes have been proposed for image denoising. For example, total variation (TV), which is a very popular prior for natural images, has been widely used for Gaussian and Poisson denoising [1,2]. However, TV prior is known to result in stair-casing artifacts [3], and thus other image priors such as the Lyskaer-Lundervold-Tai (LLT) model [3], total generalized variation (TGA) [4], fractional-order total variation [5], and deep image prior [6] have been used to reduce the stair-casing artifacts for Gaussian or Poisson denoising. Furthermore, in other applications such as medical imaging or astronomy photography, the resulting images usually have different general features from natural images, and thus should benefit from other types of priors such as the L1-norm which promotes sparsity [7].

## Project overview

Here I propose to evaluate a few different image priors within an ADMM-based framework on real experimental Poissonian images with distinct features. Specifically, I will assume that Poisson noise in the only source of noise in the image and implement the data fidelity term accordingly. As for the image priors, I plan to implement L1-norm prior (assuming sparsity in the zeroth order derivative), TV prior (assuming sparsity in the first order derivative) and LLT prior (assuming sparsity in the second order derivative) [3].

Furthermore, the experimental data used for evaluating the denoisers will be collected using an EMCCD camera in the lab. The deep-cooled EMCCD camera should eliminate most of the thermal noise and read noise, leaving the Poisson noise the dominate noise in the low-light images. Specifically, I will collect the following sets of low-light images with distinct features:

1) Natural scenes (e.g. people, daily objects);
2) Microscopic images of USAF resolution target;
3) Microscopic images of persistent luminescent microparticles (also known as glow in the dark materials, which can emit light for a few hours after the excitation has ceased).

The low-light requirement can be achieved with a dim illumination source combined with neutral density filters, small aperture sizes or extremely short exposure time. Additionally, a “ground-truth”/bright image corresponding to each of the low-light image above will also be collected by using a much stronger illumination condition or a longer exposure time.

As for the denoiser evaluation, both the qualitative and quantitative criteria will be adapted. On one hand, the denoised images from different denoisers will be visually compared with low-light images and the “ground-truth” images for evaluation. On the other hand, the PSNR values between the denoised images and the “ground-truth” images will be computed to quantitatively evaluate the denoiser performance on different types of images. Furthermore, I will also evaluate how fast each denoiser converge by calculating the convergence (the difference between sequential iteration) and the PSNR as a function of iteration number. As different image priors generalize different set of images, and three test image sets should have distinct features, I expect that the best image prior should be different for Set (1) to (3).

## Timeline and goals

2/24-2/27:

- Read through the papers about L1-norm prior, TV prior and LLT prior.
- Take the three test sets of images.

2/28-3/2:

- Assuming the noise in the image follows Poisson distribution, analytically derive the update rules for each variable under the ADMM framework for different image prior.

3/3-3/6:

- Implement the analytical update rules in Python for L1-norm prior, TV prior and LLT prior. Construct the denoisers.
- Evaluate the denoisers on the three test sets of images qualitatively and quantitatively as discussed above.

3/7-3/9:

- Summarize the results.
- Work on the poster and the report.

## Reference

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