Denoise Microscopic Data with Deep Learning

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Abstract

Microscopic Images often suffer from noise due to several factors like low lightening, vibration, limitations of the imaging sensor. Our study addresses this issue of noise in microscopic images and uses several Non Deep Learning and Deep Learning approaches to mitigate that noise, using datasets like LiveCell, Convollaria, Mouse actin. The aim of our project is to find the best method for denoising of microscopic images. We compare the feasibility of DL and Non-DL approaches on our dataset. Our study provides valuable insights into various noise reduction techniques.

1 Introduction

Denoising is the process of removing noise or reducing noise to the possible extent. Getting noise in microscopic images is very common due to several factors such as low light conditions in order to avoid phototoxicity and limitations of the imaging sensors. So it is very difficult to get microscopic images without noise. In our study we try to address this problem and use several techniques. We use LiveCell, Mouse actin dataset to conduct our experiment and the authors of the paper (1) used the data from the book “The beetle” to find the best standard deviation of Gaussian PSF. We use both Non-DL and DL approaches to conduct our study. We compare our results using Signal-to-Noise ratio (SNR) and Peak Signal-to-Noise ratio (PSNR). The higher the SNR/PSNR values, better the performance. For Non-DL approach we use Median Filter, Gaussian filter, Box Filter and Box3D Filter to mitigate noise from the noisy images. Our DL approach was inspired by research paper “Improving Blind Spot Denoising for Microscopy” (1). We train the model for PSF values of 0.5, 1.0 and 1.5 to find which PSF works best for denoising. Thus, we try to find the best approach for denoising microscopic data using various methods.

2 Related Work

A lot of work has been carried out for denoising the microscopic images. One of them is implemented in the paper “Improving Blind Spot Denoising for Microscopy” (1). This paper uses Noise2Void as a base which is implemented in the paper "Noise2void-learning denoising from single noisy images" (2). To reduce the noise some different approaches have been used such as Masking scheme to implement blind spot noising (4), Pixel masking approach (5).

3 Methodolgy

3.1 Non-DL approach

On the images of Mouse actin Dataset, we used Gaussian Filter, Spatial Filter (Box Filter), Non Linear Spatial Filter (Median Filter) and Box3d Filter to remove the noise. Gaussian Filter smooths out using convolution operator to remove details such as noise. Box Filter is a form of low pass filter which averages the pixel value based on neighbouring pixels. Median Filter finds out average of pixel values within a window. Box3D Filter operates by averaging the values of 3D pixels. We implemented these filters to denoise the images using the OpenCV library in Python.

3.2 DL approach

Our Deep Learning approach is an implementation of the model from “Improving Blind Spot Denoising for Microscopy” (1). We implemented the model using PyTorch. This is a type of self-supervised learning. In this approach, the image was generated in two steps: first, they form the phantom image z, which is produced by light coming from excited molecules in the sample. Secondly, a distorted image is formed by the convolution operation $s = z * h$, where h is the known Point Spread Function (PSF) (2).

$$p_{NM}(x|s) = \prod_i p_{NM}(x_i, s_i), \tag{1}$$

The authors of (1) describe that they used Noise2Void (3) as a starting point and built upon it. The latter used a U-Net architecture to predict the clean signal from a noisy image, excluding the pixel being predicted. They (1) introduced the Point Spread Function (PSF) to the network's output to address the high-frequency artifact problem with Noise2Void and to ensure that the resulting images are smooth. In Noise2Void the signal for each pixel is being predicted by considering its surrounding patch and ignoring the pixel itself

$$s^i = f(x_i; \theta)$$

but in a blind spot receptive field pixel which is being predicted is being ignored so that noisy pixels are not copied by the network

$$\sum_i (\hat{s}_i - x_i)^2$$

Blind spot methods like Noise2Void sometimes produce high-frequency artifacts, which are unrealistic, because details are due to PSF. To solve this they added PSF convolution step after the U-Net model on the phantom image. By doing this it can be assured that the final output is free of unrealistic high frequencies. An extra loss term was introduced in their model to penalize the negative values. This extra loss term works with the original loss from Noise2Void to ensure that the phantom image is physically plausible.

$$|M| \left(\hat{s}_i - x_i\right) + \lambda_N \max(0, -\hat{z}_i) \tag{2}$$

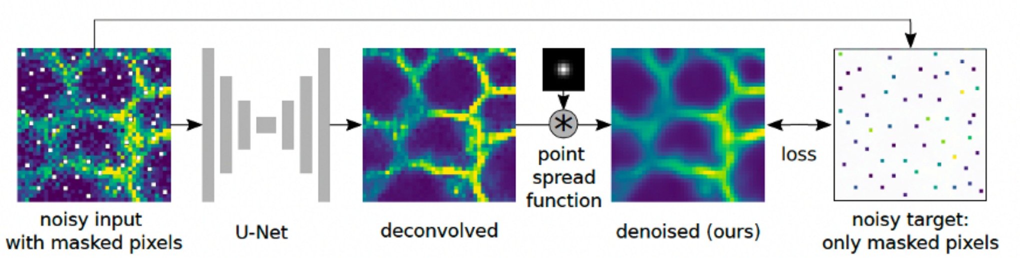

Figure 1: Architecture of the model (1)

4 Training

We use 3 depths of U-Net with 1 input channel. The model was trained for 200 epochs.The initial learning rate used to train our model is 0.001. The optimizer we use is Adam Optimizer with a batch size 1. The Positivity Constraint is set to 1. We trained for three different values of Gaussian PSF equal to 0.5, 1, and 1.5, unlike in (1) where only PSF = 1 was implemented.

5 Experiment Results

5.1 Non-DL approach

We started with using LiveCell dataset to implement our denoising approach. This LiveCell dataset was not noisy, so we added Gaussian noise with standard deviation 100 and mean 0 resulting in SNR of 13.48. We also implemented denoising on Mouse actin dataset which was already noisy with PSNR of 23.12.

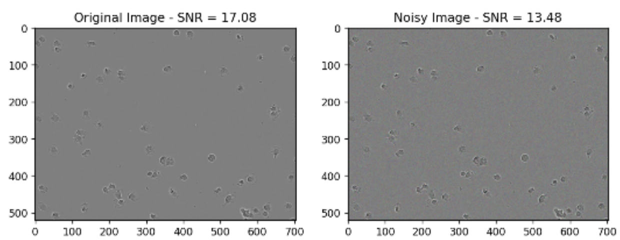

Figure 2: Original Image [left] and Noisy Image[right] of LiveCell Dataset

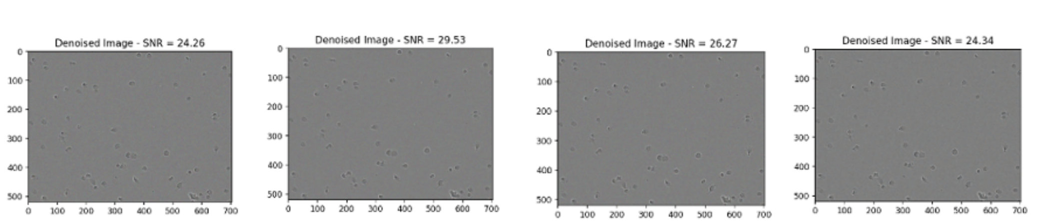

Figure 3: Results after applying Median, Gaussian, Box, Box3D Filters on LiveCell respectively

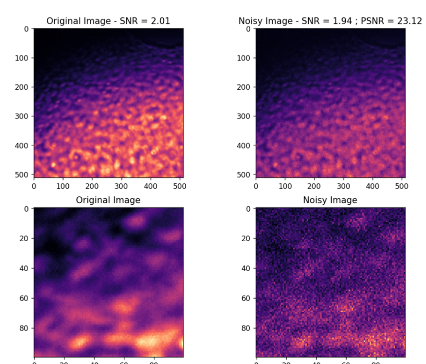

Figure 4: Ground Truth Image [left] and Noisy Image[right] of Mouse actin Dataset

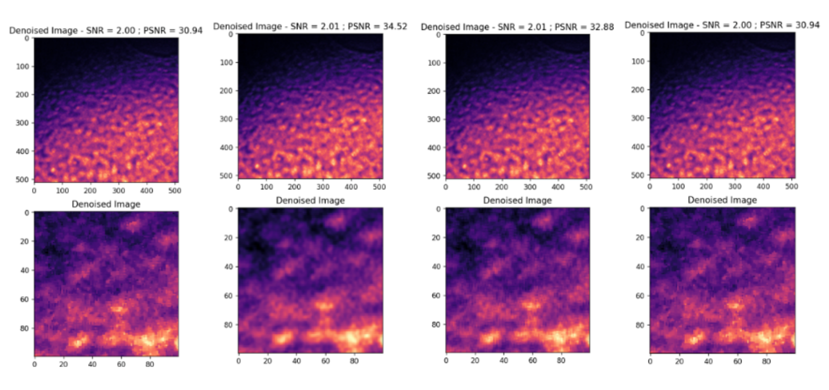

Figure 5: Results after applying Median, Gaussian, Box, Box3D Filters on Mouse actin respectively

Filter Type	Median Filter	Gaussian Filter	Box Filter	Box3D Filter
SNR Value on LiveCell	24.26	29.53	26.27	24.34
PSNR Value on Mouse Actin	30.94	34.52	32.88	30.94

Table 1: Comparison of SNR for LiveCell and PSNR for Mouse actin

We can observe that denoising works best with Gaussian Filter for both our datasets where LiveCell has SNR of 29.53 and Mouse Actin has PSNR of 34.52.

5.2 DL approach

We use Mouse Actin to compare the performance of DL and Non-DL approach because LiveCell dataset was not compatible with the DL model. We trained our model for different values of PSF that is 0.5, 1.0, 1.5. Noisy image has PSNR of 23.12.

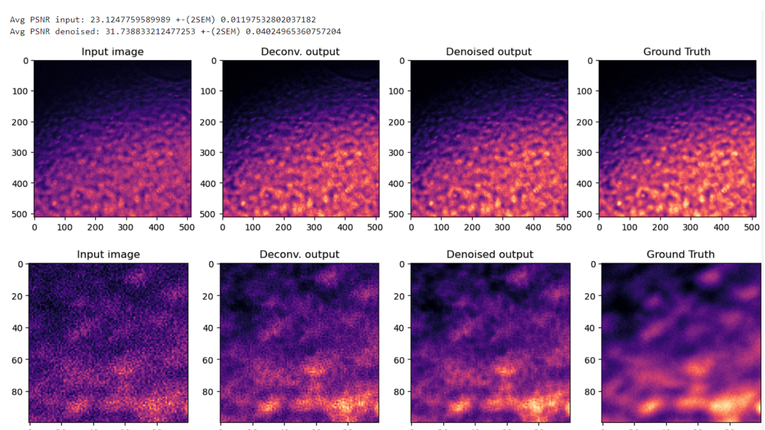

Figure 6: Denoising with PSF=0.5

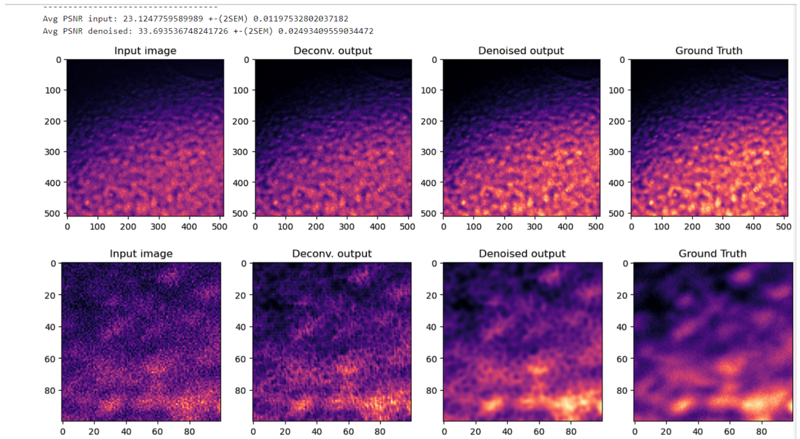

Figure 7: Denoising with PSF=1

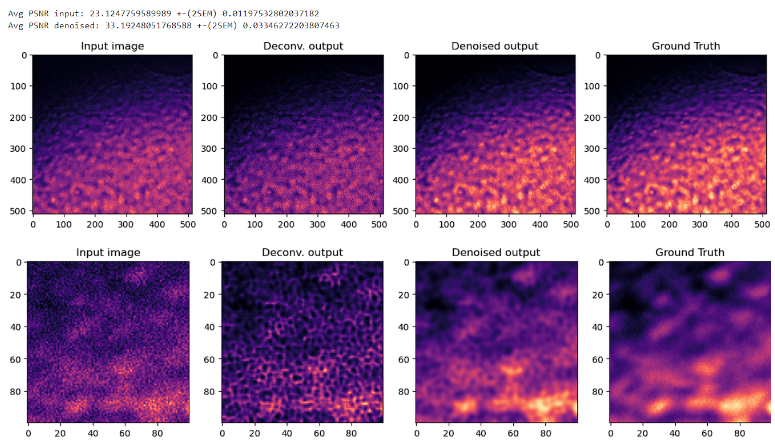

Figure 8: Denoising with PSF=1.5

PSF	0.5	1	1.5
PSNR Value	31.73	33.69	33.19

Table 2: Comparison of PSNR Values for Different PSF values

We can observe that denoising works best with PSF=1 which results in PSNR of 33.69.

6 Conclusion

We used both Non-DL and DL approaches to diminish the noise from microscopic images. We used non-DL filters like median, Gaussian, Box and Box3D filters and DL approach inspired by "Improving Blind Spot Denoising for Microscopy"(1). We trained using PSF values of 0.5, 1 and 1.5 and evaluated our results. So, we conclude that the best non-DL approach is Gaussian Filter with PSNR of 34.52, the best DL denoising is with PSF = 1 with PSNR of 33.69. Furthermore, the Gaussian Filter works best overall for Mouse actin dataset.

References

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