Comparing deep learning and traditional denoising methods for voltage imaging

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1. Introduction

The brain is one of the most complex biological systems of the body. To truly understand how it works, we need to observe activity at the level of individual neurons. Fluorescence voltage imaging enables this, offering high-resolution insights into neural signals. However, its accuracy is limited by shot noise, which distorts the signal when photon counts are low. Overcoming this challenge is the key to unlocking the brain's complex inner workings.

Voltage imaging is a technique that allows for high-resolution recording of neuron activity. but it often suffers from low signal-to-noise ratios (SNR) primarily due to photon shot noise. Traditional denoising methods, such as Variance Stabilizing Transformation (VST) and Penalized Matrix Decomposition (PMD), have been used effectively in the past.

Recently, deep learning-based denoising methods, like CellMincer, have emerged as promising alternatives because they can learn complex signal models without requiring clean training data. This paper compares the performance of traditional and deep learning methods for denoising voltage imaging data using both a synthetic and in vivo dataset. The evaluation utilizes the metrics SNR, PSNR, and tSNR.

This comparative study aims to highlight the potential and limitations of deep learning approaches and suggest future improvements.

2. Research Question

What deep learning-based denoising methods can be effectively applied to microscopy and voltage imaging, and how do they compare to traditional techniques?

Subquestion:

- What traditional denoising methods are used for denoising voltage imaging?
- What deep learning-based denoising methods can be used for denoising of voltage imaging?
- How do deep learning-based and traditional methods perform in denoising voltage imaging data, as measured by improvements in signal-to-noise ratio?

3. Methodology

Traditional Methods:

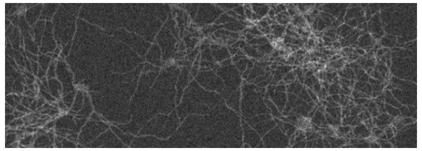
- VST (Variance Stabilizing Transformation): Converts signal-dependent noise into approximately constant Gaussian noise using the Generalized Anscombe Transformation (GAT) and a Gaussian denoiser BM3D.

- PMD (Penalized Matrix Decomposition): Decomposes the original data matrix into spatial and temporal components, leveraging the localized, structured nature of signals and uncorrelated noise to isolate and remove noise.

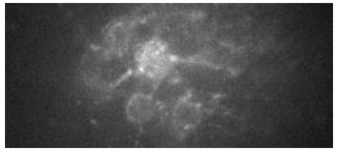
Deep learning Method:

- CellMincer: A deep learning model that uses a U-Net to extract spatial features from individual frames, followed by a temporal convolutional module that performs pixel-wise denoising using time-series embeddings.

Datasets:



Optosynth: Synthetic dataset



HPC2: : Real in vivo dataset

Evaluation metrics:

- **SNR**: Quantifies how much useful signal is present compared to the noise. A higher SNR means a cleaner, less noisy signal.
- **PSNR**: Compares peak signal to noise, less sensitive to brightness than SNR. Higher values for PSNR means less noise.
- **tSNR**: Shows how stable the signal is over time. How higher tSNR, the more stable the signal.

Setup

For this experiment the three methods denoised five of the most noisy movies of the Optosynth dataset and 2 movies of the HPC2 datasets. This combines to a total of 65000 frames per method. Optosynth being a synthetic dataset comes with a ground truth which allows for the use of the most common used metrics: SNR and PSNR. HPC2 comes without a ground truth, therefore tSNR is used as substitute metric.

4. Results

VST (a)

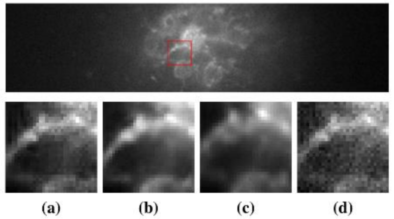
VST performed very poorly on the synthetic and in vivo datasets. Originally developed for fluorescents cell but did not generalize well to voltage imaging. On the synthetic dataset VST resulted in blurry frames.

PMD (b)

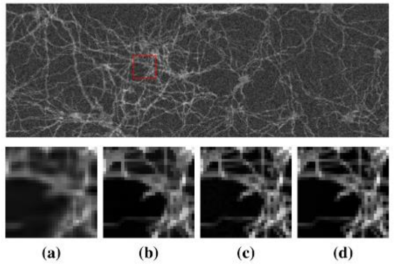
PMD was able to retain the most details in the in vivo dataset. However, this performance was not fully captured by the tSNR metric. On the synthetic dataset PMD did performed second best but its result is still very close to the ground truth.

CellMincer (c)

Great performance on the synthetic dataset, which was expected because the model was trained on similar data. The SNR and PSNR scores are nonetheless impressively high. On the in vivo data its results were slightly blurry. Its tSNR score indicated it was able to obtain a stable signal despite the blurryness. CellMincer demonstrated good generalization across different datasets without extra training.



Method	tSNR
VST	19.96
PMD	20.68
CellMincer	21.0
Original	13.98



Method	SNR	PSNR	tSNR
VST	30.74	66.87	29.59
PMD	49.48	85.6	31.47
CellMincer	58.28	94.39	29.63
Original	33.12	69.23	16.63

5. Conclusion

- CellMincer is promising, even when trained on synthetic data
- PMD remains a strong, generalizable baseline
- VST performed very poorly
- Deep learning shows great potential but may benefit from real-data training
- tSNR alone does not fully capture the denoising performance.