Evaluating established denoising methods for voltage imaging

Comparison of SUPPORT, DeepCAD-RT, and PMD when applied to voltage imaging data

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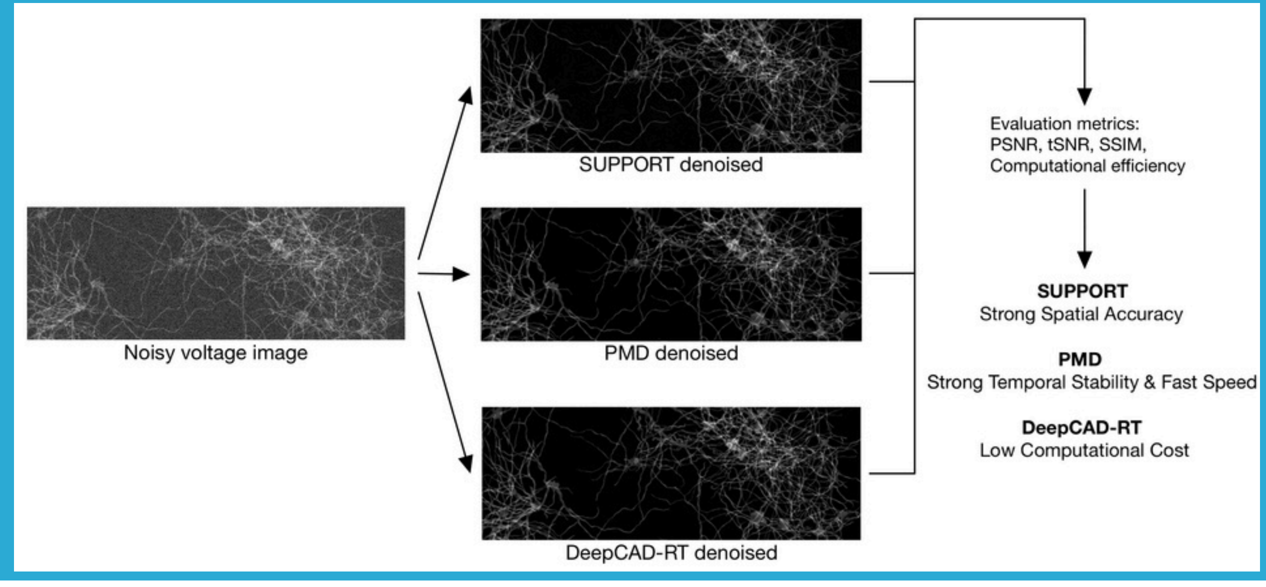
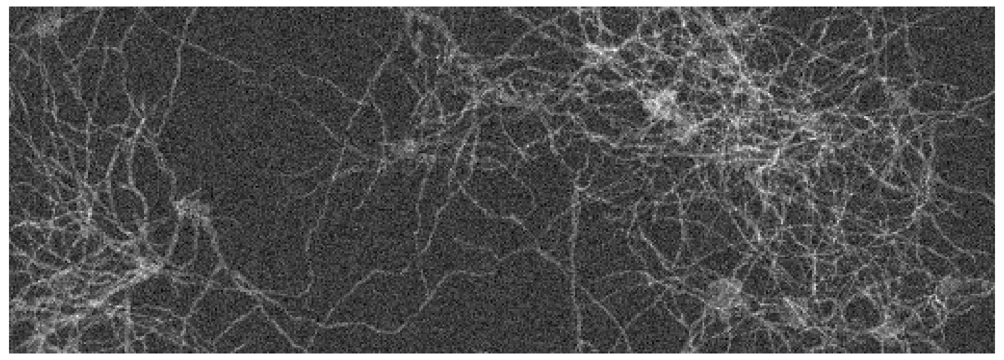
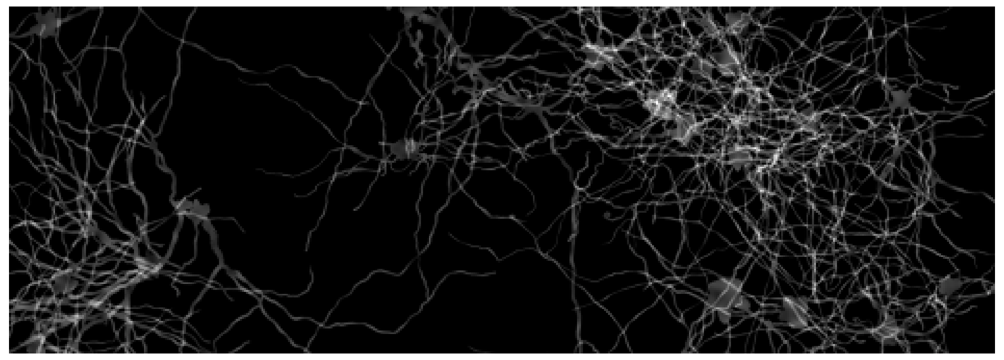


01 Background

Voltage imaging enables fast, population-scale recording of neural activity, but suffers from low signal-to-noise ratio (SNR) due to limited light level and high frame rates. Traditional denoising methods often blur spatial details or distort temporal dynamics, motivating the development of specialized techniques like SUPPORT, DeepCAD-RT, and PMD. While these methods improve reconstruction, comprehensive evaluations across noise levels, datasets, and computational costs remain limited. This work aims to systematically assess their performance to guide method selection in voltage imaging applications.



Noisy Image of SNR level 1



Clean Image

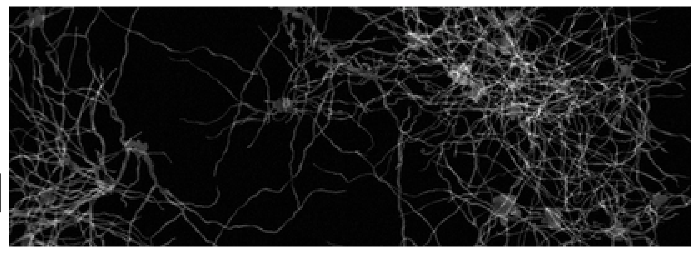
02 Research Question

How do three state-of-the-art denoising methods, SUPPORT, DeepCAD-RT, and PMD, compare in terms of spatial performance, temporal stability, and computational efficiency when applied to voltage imaging data with varying levels of noise?

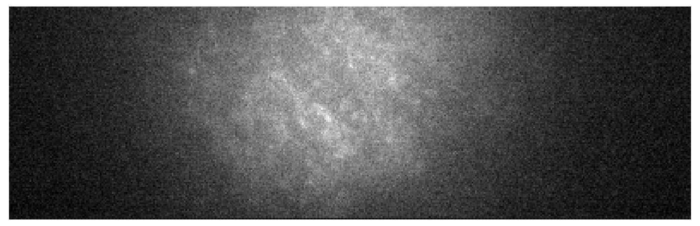
03 Methodology

Datasets

- Synthetic dataset
  - Generated by Optosynth [4]
  - Four SNR levels
- Real dataset
  - Publicly available [5]
  - No ground truth



Noisy image of SNR level 4 in the synthetic dataset



Noisy image in the real dataset

Evaluation Metrics

- Peak SNR (PSNR)
  - The ratio between the maximum value and the mean squared error between the denoised image and the ground truth.

$$10\log_{10}\left(\frac{I_{\max}}{\frac{1}{WH}\sum_{x=1}^{W}\sum_{y=1}^{H}[X(x,y)-Y(x,y)]^2}\right)$$

  - Measure spatial fidelity, requires ground truth
  - Higher means better spatial fidelity
- Structural similarity (SSIM) [6]
  - Evaluates image similarity based on structural information
  - Measure spatial fidelity; Does not require ground truth, used on the real dataset.
  - Ranged 0 to 1. Too close to 1 indicates no noise removed. Too close to 0 indicates overly smoothed. Ideally 0.8 ~ 0.9, indicating good spatial fideliy.
- Temporal SNR (tSNR)
  - The ratio of the temporal mean to the temporal standard deviation
  - Measure temporal performance
  - Higher means better temporal stability

$$\frac{\frac{1}{T}\sum_{t=1}^{T}x_t}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t-\mu)^2}}$$

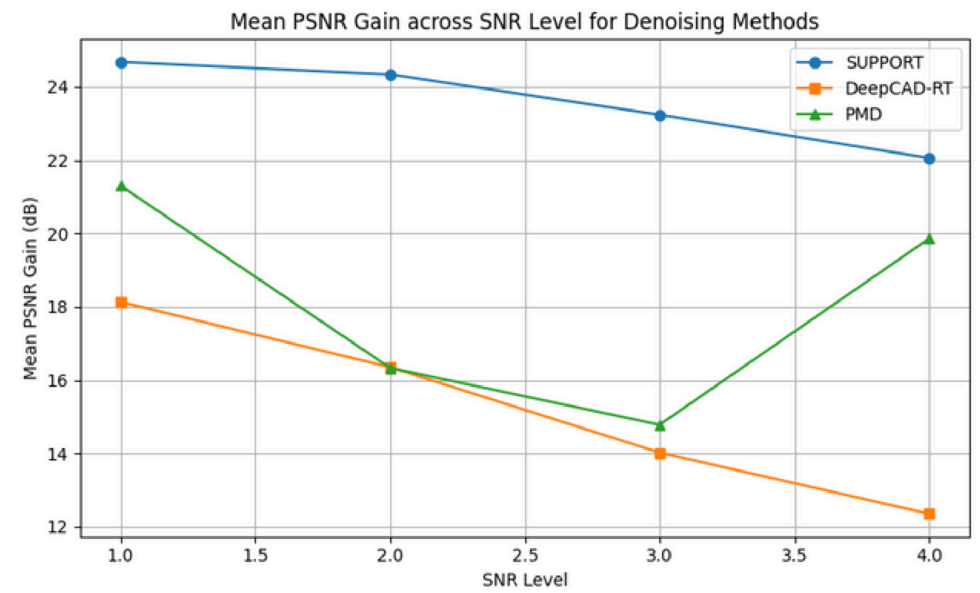
- Computational efficiency
  - Training cost (for SUPPORT and DeepCAD-RT)
  - Inference time

Denoising Methods

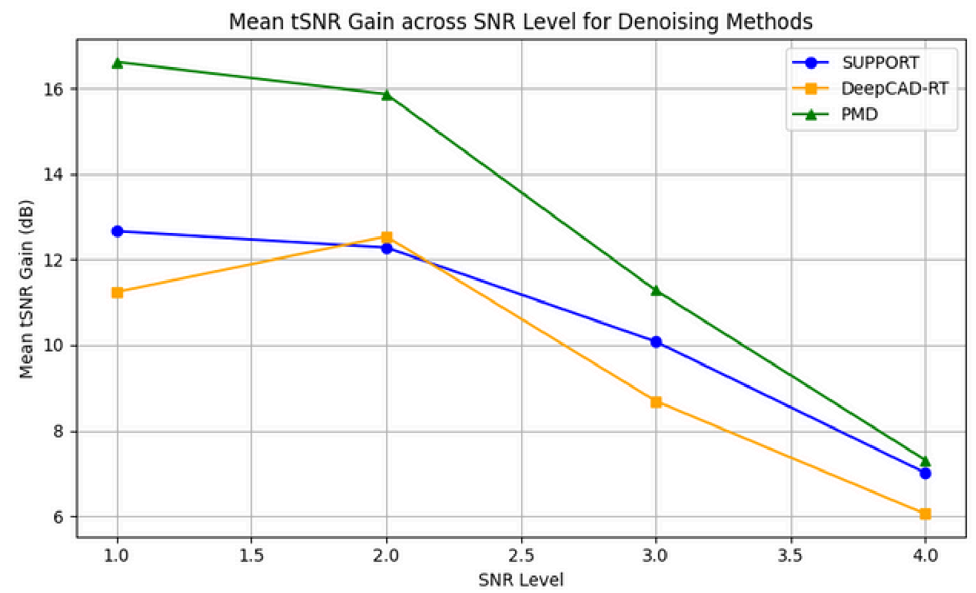
- SUPPORT [1]
  - Spatiotemporal patch-based deep learning, self-supervised
  - Strong noise suppression with high spatial fidelity
- DeepCAD-RT [2]
  - Deep CNN-based real-time denoising model, self-supervised
  - Optimized for temporal continuity
- PMD [3]
  - Non-learning, model-based method, sparse decomposition
  - Interpretable and efficient

04 Results

Synthetic dataset



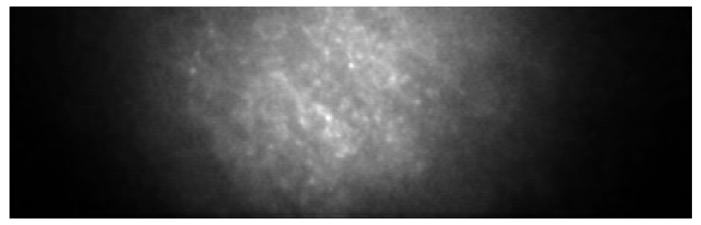
SUPPORT is robust to varying noise conditions, while PMD shows better results than DeepCAD-RT, especially when denoising data with high SNR.



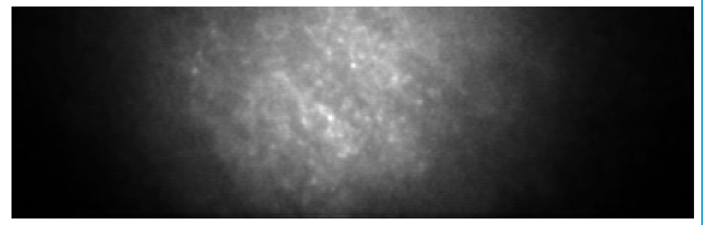
PMD is most effective across all SNR levels, particularly at lower SNR, whereas the advantage decreases as the data becomes less noisy.

Real dataset

SUPPORT denoised image



DeepCAD-RT denoised image



PMD denoised image

Method	Mean tSNR Gain (dB)	Mean SSIM
SUPPORT	4.37	0.915
DeepCAD-RT	4.36	0.922
PMD	4.42	0.918

All three methods yield comparable tSNR gains on the real dataset, with PMD showing the highest tSNR and DeepCAD-RT achieving the best structural similarity. Gap is too small to draw any strong conclusion.

Computational Efficiency

Method	Peak Memory (GB)	Training Speed (patch/s)	Inference Speed (samples/s)
SUPPORT	5.5	1.21	9.36
DeepCAD-RT	3.7	3.12	19.44
PMD	–	–	52.26

DeepCAD-RT not only trains faster and with lower memory usage than SUPPORT, but also achieves a higher inference speed. PMD outperforms both methods, offering the fastest inference among the three.

05 Conclusion

- SUPPORT
  - Strong in spatial fidelity
  - High training cost and inference time
- DeepCAD-RT
  - Low training cost and inference time
  - Not as robust in temporal and spatial performance
- PMD
  - Strong in temporal performance and speed
  - Less robust in spatial fidelity

06 Future Work

- Refining evaluation metrics
  - Include task-specific or biologically grounded criteria (e.g. spike detection)
- Exploring datasets with annotated regions of interest
  - Focus on the part of the image more meaningful biologically
- Expanding the scope of datasets
  - Consider recordings from different ainimal/regions, imaging modalities (e.g., two-photon vs. widefield)

Reference
[1] Minho Eom el al. Statistically unbiased prediction enables accurate denoising of voltage imaging data. Nature Methods, 20, 2023.
[2] Xinyang Li et al. Real-time denoising enables high-sensitivity fluorescence time-lapse imaging beyond the shot-noise limit. Nature Biotechnology, 41, 2022
[3] E. Kelly Buchanan et al. Penalized matrix decomposition for denoising, compression, and improved demixing of functional imaging data. bioRxiv, 2019.
[4] Mehrtash Babadi. Optosynth. https://github.com/cellarium-ai/Optosynth, 2021.
[5] Y. Bando, Real-time Neuron Segmentation for Voltage Imaging. Zenodo, Oct. 23, 2023. doi: 10.5281/zenodo.10020273.
[6] Zhou Wang et al. Image quality assessment: from error visibility to structural similarity. IEEE Transactions on Image Processing, 13(4):600–612, 2004.