TRNS Stochastic Damping

EEG Denoising

CHB-MIT Pediatric Epilepsy Dataset

1. Objective

This study evaluates a training-free TRNS operator for cleaning real clinical pediatric EEG while reducing background variability and protecting transient morphology. Continuous pediatric EEG is routinely contaminated by movement, electrode, and muscle artifacts. High noise levels drive false alarms in seizure-detection systems; aggressive filtering, conversely, can attenuate or reshape the spikes and sharp waves that both clinicians and algorithms must recognise. An operator that reduces background variability without destroying transient morphology therefore addresses two practical problems at once.

2. Dataset

A sixty-second excerpt was taken from the CHB-MIT Scalp EEG Database (PhysioNet), recording chb01_03.edf, channel FP1-F7 (start time 300 s). The segment contains the mixture of artifacts commonly encountered during long-term pediatric monitoring.

3. Method

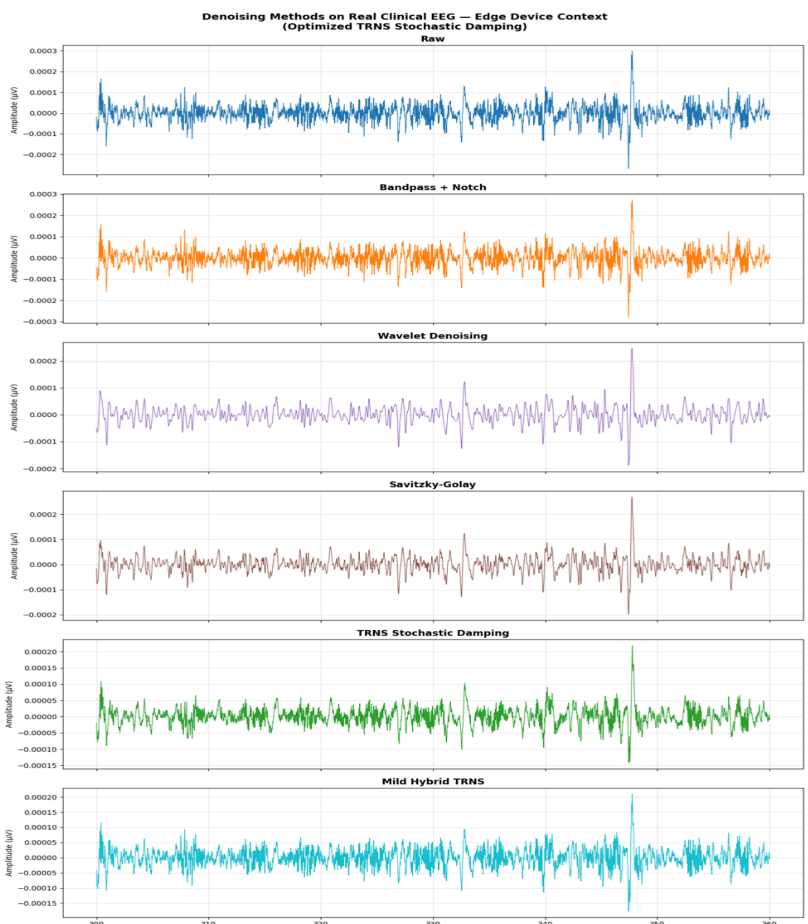
The operator was compared with a clinical-standard bandpass-plus-notch cascade, wavelet denoising, and Savitzky–Golay smoothing. A milder hybrid form (light pre-filtering followed by TRNS) was also evaluated. Quantitative metrics covered variability reduction, high-frequency noise reduction (30–128 Hz), low-frequency content preservation (0.5–30 Hz), and peak-amplitude change. Spike and transient morphology were inspected visually.

4. Results

Method	Variability Red.	HF Noise Red.	LF Preservation
Bandpass + Notch	2.25%	18.75%	98.71%
Wavelet	17.72%	99.78%	65.39%
Savitzky–Golay	14.96%	99.60%	69.79%
TRNS	**29.38%**	64.10%	46.11%
Mild Hybrid TRNS	21.78%	47.20%	62.29%

TRNS records the strongest variability reduction while remaining competitive on high-frequency noise suppression.

Figure 1. Denoising methods on real clinical EEG (CHB-MIT chb01_03, FP1-F7, 300–360 s). Top to bottom: Raw, Bandpass + Notch, Wavelet, Savitzky–Golay, TRNS Stochastic Damping, Mild Hybrid TRNS.



5. Interpretation

Variability reduction is the metric most directly linked to false-alarm rates in long-term monitoring. TRNS led on this measure (29.38%) while still suppressing a substantial fraction of high-frequency noise (64.10%). Visual inspection of the large transient near 348–350 s confirms that spike amplitude and shape remained recognisable, indicating that the reduction in background activity did not come at the cost of clinically critical transients.

The milder hybrid form trades some variability reduction for higher low-frequency preservation and may be preferred when baseline integrity is the higher priority. Classical methods either leave most of the background intact (Bandpass + Notch) or achieve strong noise reduction at the expense of greater morphological attenuation (Wavelet, Savitzky–Golay).

6. Positioning

Candidate for edge and wearable long-term EEG systems that must simultaneously lower false alarms and protect morphological detail. The training-free formulation and modest computational profile make the operator suitable for resource-constrained continuous monitoring.

7. Limitations

Results are reported on a single sixty-second segment from one CHB-MIT recording under the conditions of the accompanying Colab. Performance on longer ambulatory recordings, different channels, or other noise compositions may vary. Processing time in the current implementation is higher than classical filters; further optimisation for real-time edge deployment remains future work.

8. Conclusion

On this real clinical pediatric EEG segment, TRNS achieved the strongest reduction in signal variability while preserving the morphology of prominent spikes and transients. These properties support its use as a practical front-end regularizer for long-term and wearable EEG monitoring.

References

Guttag, J. (2010). CHB-MIT Scalp EEG Database (version 1.0.0). PhysioNet. https://doi.org/10.13026/C2K01R

Shoeb, A. (2009). Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment. PhD Thesis, Massachusetts Institute of Technology.

Goldberger, A. L., et al. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation, 101(23), e215–e220.