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RunDAE for Enhanced Denoising of PPG Signals

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Abstract: Photoplethysmography (PPG) is vital for monitoring cardiovascular dynamics in clinical and wearable systems. However, PPG signals are highly susceptible to noise, especially during movement. The three primary sources of interference are: baseline wander, muscle artifacts, and Gaussian white noise. The vulnerability of PPG to these artifacts complicates its reliable use in real-world conditions. To remove these noises and ensure PPG signal fidelity, this study leverages sample-by-sample denoising using two Running Denoising Autoencoder architectures: a fully connected model (RunDAE) and a convolutional (RunCDAE). These models are evaluated on real PPG recordings with varying segment lengths, corrupted by additive mixtures of noise at multiple input signal-to-noise ratios. Performance metric, i.e., SNR improvement, demonstrates that the RunDAE significantly enhances signal quality while preserving morphological features of PPG waveforms.

I. Introduction

Photoplethysmography (PPG) is widely utilized in both wearable and clinical devices for capturing vital signs such as heart rate, respiration rate, and oxygen saturation. In wearable applications in particular, the recorded PPG signal is frequently contaminated by high-frequency disturbances originating from muscle contractions, known as motion artifact (MA) [1], and low-frequency fluctuations caused by respiration or slow movements, referred to as baseline wandering (BW) [1]. This degradation arises directly from the continuous movement of the subject during recording. In addition, Gaussian noise may also be superimposed on the PPG signal as a result of sensor electronics or thermal sources. Such noise sources can introduce significant errors in estimating vital signs, including heart rate variability, oxygen saturation, and blood pressure.
Several denoising autoencoder (DAE) architectures show strong potential for biomedical signal enhancement [2–4]; however, the classical DAE's non-overlapped segments processing may introduce discontinuities at segment boundaries, an artifact that limits its reliability in real applications. The recently proposed Running DAE (RunDAE) model addresses this limitation by leveraging recurrent neighborhood learning [4], achieving notable success in ECG denoising. Since PPG signals exhibit similar temporal characteristics, this study investigates the application of RunDAE for PPG denoising to enhance robustness under challenging noise conditions.

II. Material and methods

II.I. Running Denoising Autoencoder (RunDAE)

The classical DAE employs a symmetric encoder–decoder structure in which the noisy input segment of size N is progressively compressed through a series of dense layers with $N/2$, $N/4$, and $N/8$ units to form a latent representation. The decoder mirrors this hierarchy by expanding the latent vector through layers of $N/4$ and $N/2$, followed by an output layer with N units, thereby reconstructing a denoised segment with the same length as the input (Fig. 1A). The RunDAE model shares the same encoder as the classical DAE but differs in its output stage, where the decoder is replaced with a single linear unit to produce one denoised sample at each step (Fig. 1B).

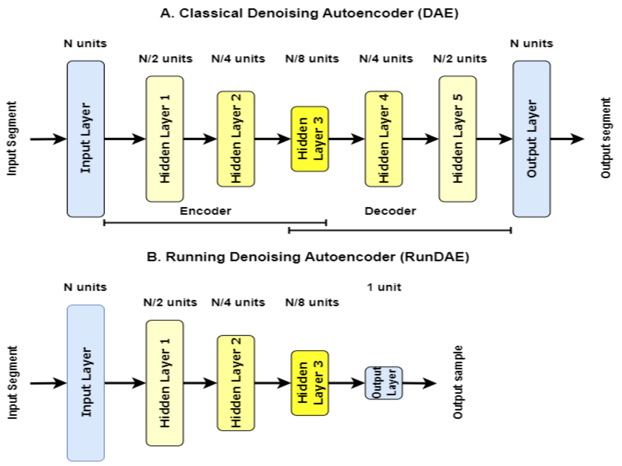


Figure 1: Architecture of A. classical denoising autoencoder (DAE), and B. running denoising autoencoder (RunDAE) .

For the convolutional denoising autoencoder (CDAE), the encoder is composed of three Conv1D hidden layers with increasing filter number (16, 32, and 64), stride = 2, and zero padding, which progressively reduce the temporal resolution from $N \rightarrow N/2 \rightarrow N/4 \rightarrow N/8$. The resulting multichannel feature map forms the latent representation. The decoder symmetrically reconstructs the signal using Conv1DTranspose hidden layers that expands the representation back to the original length, ending with a final transposed convolution layer with one filter to generate the denoised output segment. All models used linear activation in the input and output layers and ReLU activation in the hidden layers.

II.II. Data preparation

PPG signals were obtained from the BIDMC PPG and Respiration Dataset [5], which includes 53 recordings sampled at 125 Hz. After visual inspection, 50 clean recordings were retained and cropped to 30 s (3750 samples) each. Signals were band-pass filtered (3rd-order Butterworth, 0.5–10 Hz), and normalized by dividing each signal by its maximum amplitude, ensuring uniform scaling and enhancing stability during model training.

To simulate real-world conditions, recordings were corrupted with a composite noise model of baseline wander (BW), muscle artifact (MA), and Gaussian white noise (GWN) sourced from the MIT-BIH Noise Stress Test Database [6]:

$$Noise = 0.6\,BW + 0.35\,MA + 0.05\,GWN, \qquad (1)$$

reflecting the typical dominance of respiratory/slow movement drift, moderate muscle interference, and minor sensor/thermal noise. Noise was scaled to multiple SNR levels for model training (−5, 0, 15, ∞ dB) and testing (−6, 0, 6, 12 dB), with 40 recordings used for training and 10 for testing.

For the running autoencoder framework, each noisy recording was segmented into windows of N samples with N−1 overlap, preserving continuity and providing detailed temporal information for high-fidelity denoising.

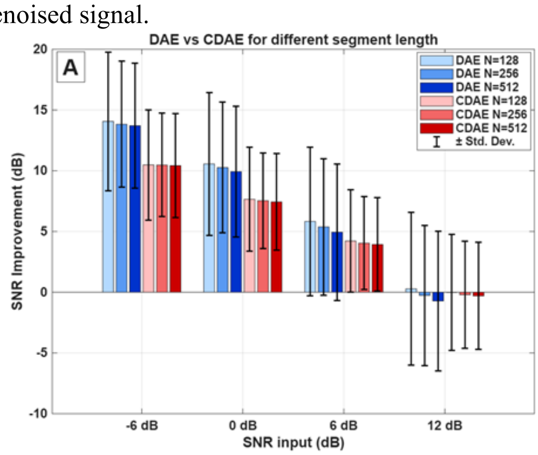
III. Results and discussion

All proposed models were trained with Adam optimizer (learning rate 10^{-4}, epoch=100, batch size=32) and mean square error as a loss function. The performance of classical and running DAE models with different segment length (N=128, 256 and 512 samples) were evaluated by signal-to-noise ratio improvement, calculated as follow,

$$SNR_{improvment} = 10\, log_{10}\left(\frac{\sum_{n=1}^{N} |\hat{x}[n]-x[n]|^2}{\sum_{n=1}^{N} |y[n]-x[n]|^2}\right). \qquad (2)$$

Where $x[n]$ is the original ECG segment and $\hat{x}[n]$ is the noisy ECG segment and $y[n]$ is the denoised output. A higher SNR improvement indicates better noise reduction performance.

The DAE/CDAE performance surprisingly drops as input SNR increases (see Fig. 2A), and introduces noticeable discontinuities or "jumps" at the 128-sample segment boundaries (see Fig. 3). In contrast, the RunDAE/RunCDAE models offer consistently higher, more stable SNR improvements across all noise levels while producing a smooth, continuous, and artifact-free denoised signal.



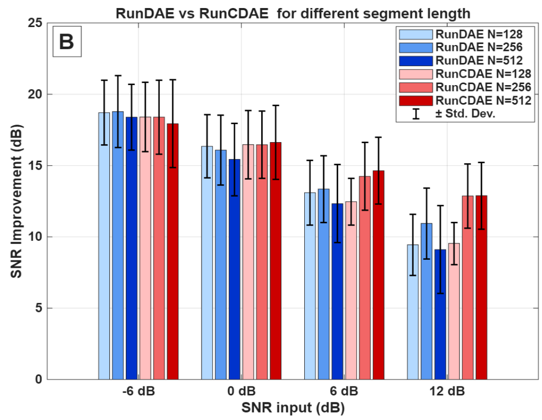


Figure 2: Average denoising performance on the testing set for (A) classical denoising autoencoder (DAE) models and (B) running denoising autoencoder (RunDAE) models under different segment lengths.

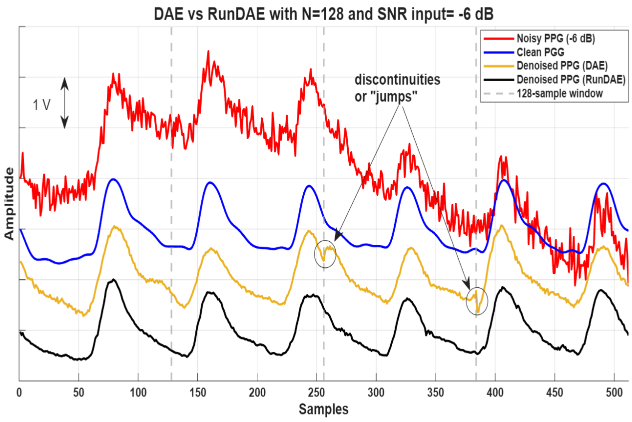


Figure 3: Comparison of noisy, clean, and denoised PPG signals using DAE and RunDAE (N=128, SNR input = –6 dB).

IV. Conclusions

This study successfully demonstrates that RunDAE models can be significantly more effective than conventional DAE/CDAE models in noise suppression in PPG signals. The RunDAEs achieve consistently higher and more stable SNR improvements across various noise level. Crucially, the RunDAE architecture eliminates the discontinuities introduced by the classical DAE, yielding a smooth, continuous, and physiologically realistic denoised output.

AUTHOR'S STATEMENT

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REFERENCES

[1] E. Mejía-Mejía and P. A. Kyriacou, *Effects of noise and filtering strategies on the extraction of pulse rate variability from photoplethysmograms*, Biomed. Signal Process. Control, vol. 80, p. 104291, doi: 10.1016/j.bspc.2022.104291.
[2] S.-C. Lai et al., Wang, *Enhanced Noise Reduction in Photoplethysmography Signals Using a Denoising Autoencoder*, Sensors and Materials, vol. 37, no. 11, pp. 5123–5139.
[3] I. Chiu, Y.-T. Liu, K.-C. Wang, H.-Y. Wei, and Y. Tsao, *Robust Photoplethysmography Signal Denoising via Mamba Networks*, arXiv. doi: 10.48550/ARXIV.2510.11058.
[4] F. Samann and T. Schanze, *RunDAE model: Running denoising autoencoder models for denoising ECG signals*, Comput. Biol. Med., vol. 166, p. 107553, doi:10.1016/j.compbiomed.2023.107553.
[5] M. Pimentel et al., "BIDMC PPG and Respiration Dataset." physionet.org, 2018. doi: 10.13026/C2208R.
[6] G. B. Moody, W. Muldrow, and R. G. Mark, "The MIT-BIH Noise Stress Test Database." physionet.org, 1992. doi: 10.13026/C2HS3T.