TransConv-DDPM: Time-Series Data Generation With Diffusion

Md Shahriar Kabir and Anne H. Ngu

The limited availability of real-world time-series data in clinical settings presents considerable obstacles to the development of effective AI models for medical diagnosis and preventative health care. In addressing this issue, generative AI models, such as generative adversarial networks (GANs) [4], [8] and variational autoencoders (VAEs) [6], have demonstrated potential in producing realistic data. Nonetheless, current methodologies frequently encounter difficulties in reconciling local and global temporal correlations, especially within chaotic physiological data. This study presents TransConv-DDPM, an advanced generative model derived from denoising diffusion probabilistic models (DDPMs) [3] to address this gap. This model incorporates multiscale convolution modules [7] and a transformer layer [5] to proficiently capture intricate temporal patterns in time-series data.

The TransConv-DDPM architecture builds on a U-Net design with two significant innovations: a transformer layer for long-range temporal relationships and multi-scale convolution modules for extracting features at different temporal resolutions. These components work together to handle the complex dynamics of physiological processes, as well as to generate realistic, diverse time-series data. The model uses the Gaussian diffusion process to gradually add and eliminate noise from data distributions, allowing for the synthesis of high-fidelity sequences. Figure 1 illustrates the training and generation processes of the TransConv-DDPM model, highlighting the diffusion and denoising steps.

Experiments were performed utilizing datasets such as the Stick Balancing dataset [2] and the SmartFallMM dataset [1]. Quantitative assessments demonstrated that TransConv-DDPM surpassed baseline models, including regular DDPMs and TimeGAN [4], across parameters such as dynamic time warping (DTW), Fréchet inception distance (FID), and Correlation Score. An ablation study highlighted the combined effectiveness of transformers and multi-scale convolutions in improving generation quality. Table 1 summarizes the results of the ablation study, highlighting the contributions of transformers and multi-scale convolutions.

In the stick-balancing dataset, TransConv-DDPM attains a correlation of 0.94, a DTW score of 96, and a FID score of 42.4, whereas TimeGAN records 0.47, 242, and 57.8, respectively. Table 2 compares the performance of TransConv-DDPM and

Digital Object Identifier 10.1109/MPULS.2025.3526507
Date of current version: 27 February 2025.

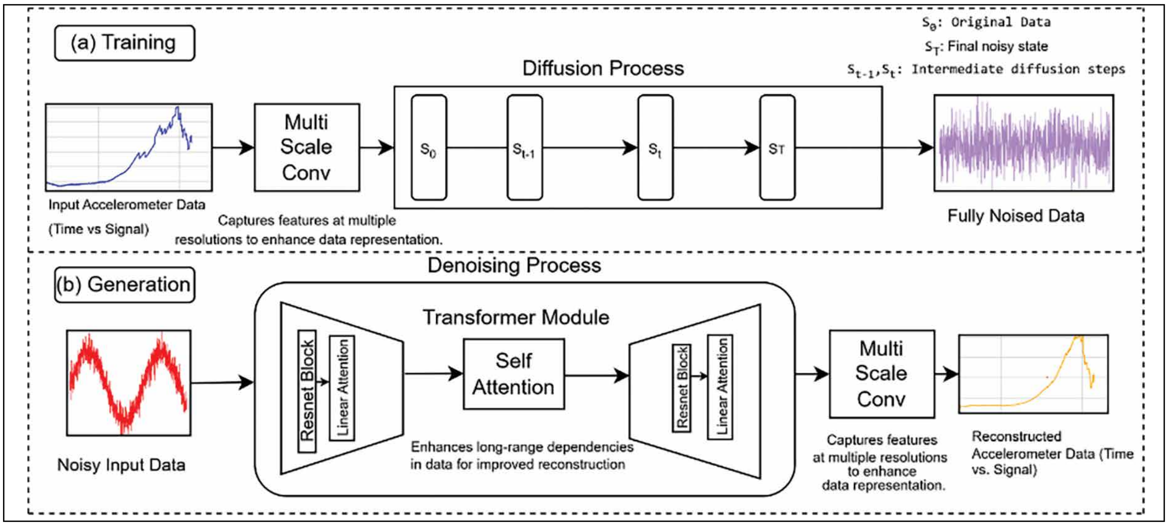

Figure 1. (a) Training: The diffusion process adds noise to the input accelerometer data for feature extraction. (b) Generation: The denoising process reconstructs accelerometer data using a transformer-enhanced model.

Table 1. Ablation study results: quantitative metrics across different model configurations on stick balance dataset.

Model	Correlation	DTW	FID
DDON(Baseline)	0.66	221	50.7
DDPL + Transformer	0.80	162	46.8
DDPM + Multi Scale Conv	0.59	99	48.5
DDPM + Transformer + Multi Scale Conv	0.94	96	42.4

Table 2. Performance comparison of TransConv and TimeGan on stick balance dataset.

Model	Correlation	DTW	FID
TransConv	0.94	96	42.4
TimeGan	0.47	242	57.8

Table 3. Performance comparison of TransConv and TimeGan on SmartFallMM dataset.

Model	Correlation	DTW	FID
TransConv	0.87	110	44.8
TimeGan	0.58	208	55.4

TimeGAN on the Stick Balance dataset. Comparable enhancements are noted in the SmartFallMM dataset, where TransConv-DDPM achieves a correlation of 0.87 along with superior DTW and FID scores, demonstrating its capacity to produce realistic and coherent data. Table 3 provides a performance comparison of TransConv-DDPM and TimeGAN on the SmartFallMM dataset.

TRANSCONV-DDPM PROFICIENTLY TACKLES the difficulties of generating intricate time-series data through the utilization of transformers and multi-scale convolutions. Its performance across datasets highlights its potential for mitigating data scarcity in clinical and other applications, paving the way for more robust AI models in time-series analysis. ■

References

[1] *SmartFallMM Dataset*. Accessed: Dec. 11, 2024. [Online]. Available: https://anonymous.4open.science/r/smartfallmm-4588/readme.md

[2] M. Debnath et al., “Pole balancing on the fingertip: Model-motivated machine learning forecasting of falls,” *Frontiers Physiol.*, vol. 15, Apr. 2024, Art. no. 1334396.

[3] J. Ho, A. Jain, and P. Abbeel, “Denoising diffusion probabilistic models,” in *Proc. Adv. Neural Inf. Process. Syst.*, 2020, pp. 6840–6851.

[4] J. Yoon, D. Jarrett, and M. Van der Schaar, “Time-series generative adversarial networks,” in *Proc. Adv. Neural Inf. Process. Syst.*, 2019, pp. 5508–5518.

[5] A. Vaswani, “Attention is all you need,” in *Proc. Adv. Neural Inf. Process. Syst.*, 2017, pp. 1–11.

[6] H. Li, S. Yu, and J. Principe, “Causal recurrent variational autoencoder for medical time series generation,” in *Proc. AAAI’23/IAAI’23/EAAI’23*, 2023, pp. 8562–8570.

[7] Z. Cui, W. Chen, and Y. Chen, “Multi-scale convolutional neural networks for time series classification,” 2016, *arXiv:1603.06995*.

[8] X. Li, “Mitigating data shortage in biomedical signal analysis: An investigation into transfer learning and generative models,” Ph.D. dissertation, Dept. Comput. Sci., Texas State Univ., San Marcos, TX, USA, Jun. 2023.

■ ***Md Shahriar Kabir*** *is currently pursuing the Ph.D. degree with the Department of Computer Science, Texas State University, San Marcos, TX, USA, specializing in generative AI and time-series data modeling.*

■ ***Anne H. Ngu*** *is currently a full professor and the Ph.D. program director with the Department of Computer Science, Texas State University, San Marcos, TX, USA. Her research focuses on machine learning, health care informatics, and cross-modal learning.*