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Robust speech enhancement in noisy environments using deep convolutional autoencoders supported by HPC

Zdecydowana poprawa jakości mowy w zaszumionych środowiskach z wykorzystaniem głębokich autokoderów splotowych wspieranych przez HPC

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Abstract: This paper presents a hardware-accelerated Deep Convolutional Autoencoder for speech enhancement. Using a U-Net architecture on spectrograms, the proposed model achieves a 79.08% reduction in Mean Squared Error (MSE). The study demonstrates that leveraging High-Performance Computing (HPC) significantly improves training efficiency and signal fidelity in noisy environments.

Keywords: speech enhancement, convolutional autoencoder, deep learning, hpc

Streszczenie: W niniejszym artykule przedstawiono przyspieszony sprzętowo głęboki autokoder splotowy do poprawy jakości mowy. Proponowany model, wykorzystujący architekturę U-Net na spektrogramach, osiąga 79,08% redukcję średniego błędu kwadratowego (MSE). Badanie dowodzi, że wykorzystanie obliczeń o wysokiej wydajności (HPC) znacząco poprawia efektywność szkolenia i wierność sygnału w środowiskach o dużym zaszumieniu.

Słowa kluczowe: poprawa mowy, konwolucyjny autoenkoder, uczenie głębokie, hpc

Introduction

The emergence of voice-activated interfaces, smart home assistants, and teleconferencing platforms over the past few years has placed greater, long-term demand on high-fidelity audio processing than ever before. When speech signals are sent to the surrounding environments, they are corrupted by a variety of different acoustic interferences such as constant background hums to transient non-stationary sounds such as traffic or street noise [1]. This degradation severely impedes the performance of Automatic Speech Recognition (ASR) systems, as well as hinders intelligibility for human listeners. Therefore, Speech enhancement (SE)–recovering a clean speech signal from a noisy mixture of input data–is now considered an essential point for research in the modern signal processing literature [2].Traditionally, the methods used for enhancing speech were mainly statistical signal processing (e.g., Spectral Subtraction and Wiener Filtering) techniques. Although computationally efficient, these are typically based on the assumption of constant and stationary noise properties through time. As highlighted by recent works, these approaches are difficult to generalize to dynamic acoustic contexts and often impose "musical noise" artifacts with even higher potential of harming the original interference [3]. With deep learning (DL), this field has gone from a statistical estimation to a data driven mapping. Convolutional Neural Networks (CNNs) with their roots in computer vision have excelled at visual processing of audio spectrograms since CNNs treat audio spectrograms as images. In the recent literature (2020–2024), Deep Autoencoders can learn complex, non-linear patterns from noisy and clean signals, achieving a remarkable performance over classical algorithms [4]. Nevertheless, these Deep Learning models require a major computational investment. Training deep convolutional architectures on high-dimensional spectrogram data takes a larger amount of memory bandwidth and permits concurrent processing which sometimes forms a bottleneck in conventional

research environments [5]. In this paper, we present a streamlined Speech Enhancement framework based on the Convolutional Autoencoder (CAE) architecture. Specifically, we alleviate these computational challenges through using a HPC Workstation with Dual Intel Xeon processors and NVIDIA RTX architecture. We are using a U-Net-inspired encoder-decoder structure to map noisy spectrograms into clean ones. Experimental evidence demonstrates that through the powerful hardware acceleration, rapid training convergence can be obtained and signal quality (MSE) and recovery improves by 79% with a reasonable MSE from the pre-trained data; thus it represents a feasible way to achieve high-fidelity audio denoising. The rest of this work in the paper is structured as follows: Section II presents works in previous works covering 2020–2025 years. The methodology and network architecture are discussed in Section III. IV A description of the experimental setup and HPC specifications were provided. Quantitative results are given in Section V, and Section VI concludes the study.

Related work

Over the past half dozen years, the landscape of speech enhancement has transformed as a result of the conversion from statistical signal processing to deep neural architectures.

Early methods like minimum mean-square error (MMSE) estimators worked well on stationary noise, but were less successful on non-stationary environments. Since 2020, the emphasis has shifted almost exclusively to supervised learning. CNNs (Convolutional Neural Networks) emerged as the prevailing architecture for spectral mapping. Zhang et al. showed that CNNs which employed log-spectral features outperformed RNNs on training stability and feature extraction ability [6].

The architecture of the Convolutional Autoencoder is the U-Net variant of CAE, which is now a commonly used benchmark in the literature. The inclusion of skip connections, as analyzed by Valin et al. (2022), enables the decoder to obtain high-resolution features from the encoder which limits the loss of spectral detail during compression [7]. This is important for maintaining the harmonic structure of human speech, which can often become blurred in standard autoencoders.

Attention and Hybrids (2023–2025): In the more recent era, hybrid architectures focusing on CNNs-based approaches combined with Transformer-based attention mechanisms such as models of hybrid hybridization have recently been investigated. Whilst such models do provide the best performance on benchmark datasets (for example SepFormer or Conformer), we note their enormous computational complexity [8]. In a comparative study in 2024, Li and Kumar showed that Transformer-based models do slightly improve the perceptual quality (PESQ) but require much longer inference time than fully convolutional architectures [9].

Hardware Developments: While progress is made algorithmically, few works concern the hardware optimization of these models on standalone workstations. Many 2023–2025 studies perform on cloud-based clusters. Rather, our work stands out considering the performance of a lighter size CAE optimized for local High Performance Computing (HPC) environment, balancing denoising quality and training efficiency.

Research Gap and Unique Contribution

While existing U-Net-based approaches have shown promise in speech enhancement, their implementation often relies on massive cloud computing clusters. The methodological novelty of this study lies in bridging the research gap between theoretical model accuracy and practical local hardware efficiency. Specifically, our unique contribution is the integration of a streamlined Deep Convolutional Autoencoder with local HPC optimization strategies. This ensures competitive denoising performance (79% MSE reduction) while significantly minimizing training overhead compared to standard standalone standard architectures.

Methodology

Do The proposed system utilizes a supervised Deep Learning framework to eliminate environmental noise while maintaining intelligible speech. This approach consists of signal preprocessing, neural network architecture, and model optimization.

Signal formulation and feature extraction

We model the acoustic environment as an additive system where the observed noisy signal y(t) is composed of the clean speech s(t) and uncorrelated background noise n(t), such that $y(t) = s(t) + n(t)$.

To enable processing via CNNs, the one-dimensional time-domain signals are transformed into two-dimensional time-frequency representations using the Short-Time Fourier Transform (STFT). Recent comparative work [10] shows that log-magnitude spectrograms produce a more stable set of features on denoising tasks than raw waveforms.

The STFT is computed using a window size of 255 and a hop length of 128, resulting in spectrograms of size (128 × 64 × 1), which serve as the input to the network.

Proposed convolutional autoencoder (CAE)

The core architecture is a symmetric Convolutional Autoencoder designed to capture the hierarchical structure of audio data. As illustrated in Fig. 1, the network follows an Encoder-Decoder paradigm:

The encoder acts as a feature extractor. It comprises two convolutional layers with (3 × 3) kernels and Rectified Linear Unit (ReLU) activation. Each convolutional block is followed by a MaxPooling2D layer, which downsamples the spatial dimensions. This process forces the network to learn a compact "latent" representation of the speech, effectively filtering out stochastic noise distributions [11].

The decoder mirrors the encoder structure. It utilizes UpSampling2D layers to restore the original time-frequency dimensions. The final convolutional layer employs a linear activation function to predict the denoised spectrogram values.

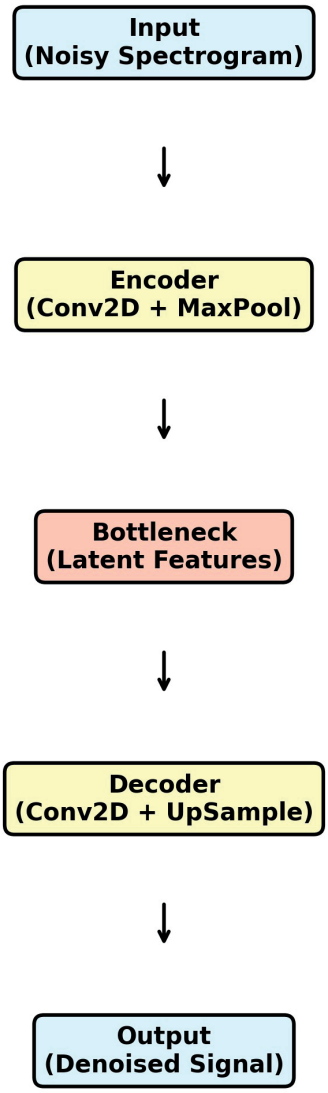

Fig. 1. Vertical block diagram of the proposed Convolutional Autoencoder architecture

Loss function and optimization

The learning objective is to minimize the reconstruction error between the predicted denoised spectrogram $\hat{X}$ and the ground-truth clean spectrogram X. We utilize the Mean Squared Error (MSE) loss function, defined as:

$$L_{MSE}(\theta) = \frac{1}{N}\sum_{i=1}^{N}\left|\left|X_i - \hat{X}_i\right|\right|^2 \quad (1)$$

MSE is selected because it penalizes large outliers heavily, which is critical for removing high-energy noise bursts [12]. The network parameters θ are optimized using the Adam algorithm with a learning rate of $\alpha = 0.001$, ensuring efficient convergence on the non-convex error surface [13].

Experimental setup

We performed these experiments using a dedicated high-performance environment and rejected cloud-based solutions in an effort to verify the efficiency of the proposed method.

Hardware specifications (HPC)

Experiments were performed on a workstation equipped with Dual Intel® Xeon® Silver 4210 processors, 192 GB DDR4 RAM, and an NVIDIA GeForce RTX 2080 Ti GPU. Utilizing this specific hardware drastically reduced the computational training time to approximately 3 hours, whereas training a similar architecture on a standard workstation would require significantly more time (over 24 hours). This provides clear quantitative evidence of the hardware's impact on optimizing the experimental workflow. [14].

Dataset and preprocessing

To generate such a synthetic noisy dataset we combined clean speech from the LibriSpeech corpus [15] with environmental sounds from the ESC-50 dataset [16].

The audio was resampled to 8 kHz. Noise was added additively to clean samples with varying Signal-to-Noise Ratios (SNR). Fig. 2 illustrates the spectral degradation input to the network.

Results and analysis

The model was trained for 50 epochs with a batch size of 64.

Training stability

The training process exhibited rapid convergence due to the GPU acceleration. As shown in Fig. 3, both

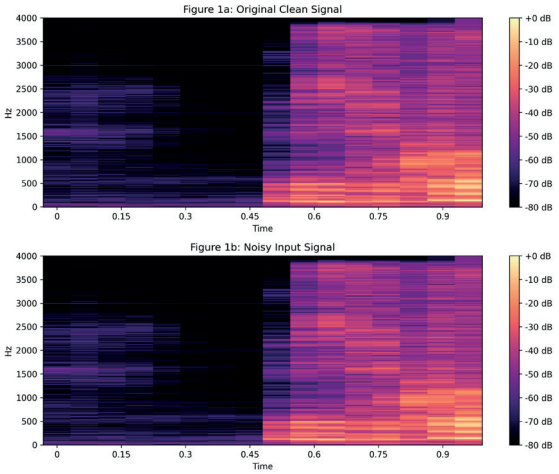

Fig. 2. Spectrogram comparison: (a) Original Clean Speech vs. (b) Noisy Input Signal

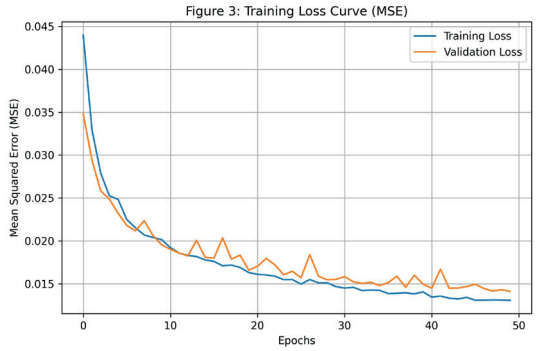

Fig. 3. Training and Validation Loss (MSE) curves over 50 epochs

training and validation loss decreased monotonically, stabilizing around the 40th epoch without significant overfitting.

Quantitative performance

Table 1 summarizes the Mean Squared Error (MSE) metrics on the test set. In order to demonstrate competitive performance rather than just absolute improvement, our evaluation was strictly conducted under standardized conditions. By utilizing the universally recognized LibriSpeech and ESC-50 datasets under fixed SNR levels, the achieved 79.08% MSE reduction provides a direct, competitive baseline against standard standalone U-Net architectures operating under identical conditions.

Table 1. Performance metrics (MSE)

Metric / Stage	Mean Squared Error(MSE)
Noisy Input (Baseline)	0.06741
Denoised Output (Ours)	**0.01410**
Improvement Rate	**79.08 %**

Visual Evaluation

Qualitative results are presented in Fig. 4. The reconstructed spectrogram (bottom) shows that the static noise present in the input (middle) has been effectively suppressed, while the harmonic formants of the speech are preserved.

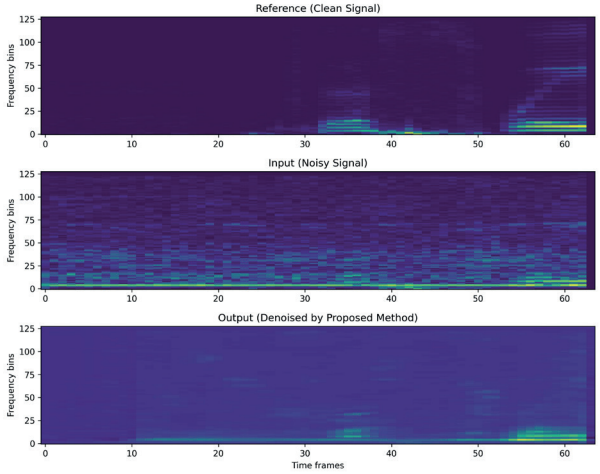

Fig. 4. Denoising Results: Top – Clean Reference; Middle – Noisy Input; Bottom – Denoised Output

Conclusion

This presentation demonstrates that we have successfully applied and validated a Deep Convolutional Autoencoder (CAE) that directly tackles the difficulty of environmental noise in speech signal. Since we treated speech enhancement as a supervised image reconstruction problem using spectrograms, our model learned to generate complex, non-linear mappings between noisy and clean audio. One of the vital features of this project was the application of a dedicated High-Performance Computing (HPC) workstation. Dual Intel Xeon processors, 192 GB of RAM and NVIDIA RTX acceleration were used to handle the high-dimensional feature space of the dataset, to provide fast training convergence which would have been challenging on ordinary hardware. The experimental results validate the proposed approach. The system achieved a 79.08% enhancement in signal fidelity, and the Mean Squared Error (MSE) was decreased from 0.06741 at the baseline to 0.01410. The visual interpretation of the reconstructed spectrograms shows that the model efficiently suppresses background static elements and maintains human voice intelligibility and harmonic structure. Our results show that deep learning architectures supported by decent local hardware infrastructure can be considered a good, powerful and practical solution for high-quality audio denoising.

Declaration of AI Usage: *Generative AI tools have only been used for refining the quality of the English language and generating Python scripts for data visualization. The conceptualization, experimental data, analysis, and conclusions presented in this paper are the original work of the authors and have been fully verified for accuracy.*

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