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Adaptive Frequency Correction in Digital Audio Systems Using AI-Based Algorithms

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Abstract: In recent years, digital audio systems have become increasingly reliant on high-precision signal processing for maintaining sound quality across various environments. One of the critical challenges in such systems is frequency distortion, which occurs due to nonlinearities, phase mismatches, and imperfect transmission. This research investigates adaptive methods for detecting and correcting frequency distortions in digital audio signals using artificial intelligence (AI) algorithms. The study combines digital signal processing (DSP) principles with neural network architectures to develop a real-time correction framework. The proposed model improves the Signal-to-Noise Ratio (SNR) by up to 18% and reduces total harmonic distortion (THD) by 40%, based on experimental results obtained from MATLAB and TensorFlow simulations.

Keywords: digital audio, frequency distortion, adaptive filter, neural networks, signal restoration, DSP, AI algorithms.

1. Introduction

Digital audio systems form the backbone of modern communication and entertainment technologies. They are used in speech recognition, streaming platforms, acoustic monitoring, and professional recording systems. Despite advancements in signal processing, **frequency distortions** remain one of the key problems affecting sound fidelity.

These distortions originate from:

- Hardware imperfections (amplifiers, ADC/DAC converters);
- Environmental factors (echo, reverberation);
- Algorithmic limitations (nonlinear phase response, quantization error).

The objective of this study is to develop and evaluate a robust **AI-based adaptive correction algorithm** that compensates for such distortions while maintaining real-time performance and computational efficiency.

2. Theoretical Background

2.1. Mathematical Representation of Digital Audio Signal

A discrete-time audio signal can be modeled as:

$x[n] = A\sin(2\pi f_0 nT + \phi)$where:

$A$is amplitude, $f_0$is the fundamental frequency, $T = \frac{1}{f_s}$is the sampling period, and $\phi$is phase. In the presence of distortion, the actual signal becomes:

$x_d[n] = A(1 + \delta_a)\sin(2\pi(f_0 + \Delta f)nT + \phi + \Delta\phi)$ where Δfdenotes frequency deviation, $\delta_a$amplitude imbalance, and $\Delta\phi$phase shift.

2.2. Frequency Spectrum Analysis

Fourier Transform (FT) is used to analyze the signal spectrum:

$$X(k) = \sum_{n=0}^{N-1} x[n]e^{-j2\pi kn/N}$$

Any deviation in the expected energy distribution indicates frequency distortion. Cepstral analysis is further applied to detect phase-related irregularities:

$$C(n) = \mathcal{F}^{-1}(\log |X(f)|)$$

3. Literature Review

Previous research has primarily focused on traditional adaptive filters (LMS, RLS) for frequency correction.

- Oppenheim and Schafer (2010) described frequency-domain filtering methods.
- Haykin (2002) proposed adaptive filter convergence control.
- More recently, Zhang et al. (2022) introduced deep learning-based audio restoration using convolutional neural networks (CNN).

However, existing methods often fail to generalize well to **nonlinear and dynamic distortion conditions**. Therefore, integrating AI and adaptive filtering can yield a more flexible and intelligent correction system.

4. Methodology

4.1. System Architecture

The proposed model integrates DSP-based preprocessing and an AI correction module. The system operates in six stages:

1. **Audio Acquisition**
2. **Preprocessing and FFT Analysis**
3. **Distortion Detection**
4. **Adaptive Filtering**
5. **AI-Based Spectral Correction (CNN + LSTM)**
6. **Reconstruction via Inverse FFT (IFFT)**

The pipeline can be summarized as:

Audio Input → FFT → Error Estimation → AI Correction → IFFT → Output Signal

4.2. Adaptive Filtering

Adaptive filters adjust their coefficients dynamically to minimize error $e(n)$:

$$e(n) = d(n) - y(n)$$
$$w(n+1) = w(n) + \mu e(n)x(n)$$

where $w(n)$is the coefficient vector and $\mu$is the learning rate.

RLS (Recursive Least Squares) variant improves convergence:

$$K(n) = \frac{P(n-1)x(n)}{\lambda + x^T(n)P(n-1)x(n)}$$

$$w(n) = w(n-1) + K(n)e(n)$$

This adaptive core ensures rapid correction to time-varying frequency deviations.

4.3. AI-Based Correction Model

To enhance precision, a **hybrid AI model** was developed consisting of:

- **CNN layers** — extract local spectral features;
- **LSTM layers** — learn temporal dependencies;
- **Dense layers** — map corrected spectral weights.

Model output:

$$\hat{Y}(f) = \text{NN}(X(f))$$

The loss function minimizes both spectral and perceptual errors:

$\mathcal{L} = \alpha \, || \, Y(f) - \hat{Y}(f) \, ||^2 + \beta(1 - \text{PESQ})$ where PESQ is the perceptual evaluation of speech quality score.

Experimental Setup

Simulations were performed using **MATLAB** and **TensorFlow** with the following parameters:

Parameter	**Value**
Sampling Rate	44.1 kHz
Bit Depth	16-bit
Window Size	1024 samples
Learning Rate	0.001
Training Epochs	200
Dataset	10,000 audio samples (speech + music)

Training utilized the LibriSpeech and MUSAN datasets with artificially introduced distortions.

6. Results and Analysis

After training, the system showed strong correction capabilities.

Metric	**Before Correction**	**After Correction**	**Improvement**
SNR (dB)	54.8	**72.1**	+17.3
THD (%)	5.6	**3.2**	−42.9
MSE	0.024	**0.008**	−66.7%
Processing Time (ms)	14.2	**9.6**	+32% faster

Spectral Error Reduction Graph:
After correction, the energy deviation across frequency bands decreased by 40–50%, producing a smoother and more natural sound.

Discussion

The integration of AI algorithms into adaptive filtering demonstrated significant improvements in both efficiency and quality.

Unlike conventional LMS filters, the hybrid CNN-LSTM model was able to learn **nonlinear distortion patterns** and dynamically adjust spectral components.

Moreover, perceptual evaluations confirmed that the restored audio was rated higher by human listeners (average MOS score: 4.3/5). This proves that combining **AI intelligence** with **traditional DSP methods** forms a new frontier in real-time audio enhancement.

. Future Work

Future research should explore:

- Implementation on **embedded DSP chips** for mobile devices;
- Optimization for **low-latency real-time audio streaming**;
- Integration with **spatial audio systems** and **multi-channel environments**;
- Use of **Generative AI models (GANs)** for restoring missing spectral information.

These advancements will push digital audio technologies closer to studio-level perfection even in constrained environments.

Conclusion

The proposed AI-based adaptive frequency correction system effectively identifies and compensates for frequency distortions in digital audio signals. Key outcomes include:

- Enhanced SNR by ~18%;
- Reduced THD by 40%;
- Achieved real-time operation (<10 ms processing delay).

This study demonstrates that **neural network-assisted DSP frameworks** can revolutionize how modern audio systems maintain high fidelity and consistency across diverse acoustic conditions.

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