Optimization of Audio Coding Parameters and Adaptive Denoising Using a Convolutionally Enhanced Transformer Framework

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Abstract. With the rapid advancement of digital audio technology, this study proposes an intelligent audio processing framework to address two key challenges: storage optimization and adaptive denoising. By modeling the trade-off between sampling rate, bit depth, and compression algorithm, the system recommends optimal encoding parameters for speech and music to balance file size and audio quality. For denoising, an adaptive algorithm based on time-frequency analysis is introduced, which applies targeted strategies according to identified noise types—Wiener filtering for background noise, median filtering with spectral subtraction for burst noise, and band-stop filtering with spectral smoothing for narrowband interference. Experiments on public datasets using ΔSNR, PESQ, and STOI metrics show that the method improves both noise suppression and audio fidelity, with SNR gains of up to 5.11dB. Subjective listening confirms enhanced clarity, and robustness tests reveal stable performance under moderate noise. Overall, the framework outperforms traditional fixed-parameter methods in both efficiency and quality.

Keywords: Audio Processing, Storage Optimization, Adaptive Coding, Noise Removal, Time-Frequency Analysis.

1. Introduction

With the rapid development of AI and multimedia technologies, digital audio has become a key medium in voice communication, streaming, virtual reality, and intelligent healthcare. However, traditional audio coding and denoising methods struggle to balance audio fidelity, storage efficiency, and computational overhead, especially under high dynamic range, complex noise, and multi-terminal scenarios. The diversity of audio content and varying noise types further complicate the use of fixed coding parameters and filtering strategies. Additionally, increasing variety in audio formats and compression standards highlights the need for adaptive mechanisms based on content and environment [1].

To address these challenges, researchers have explored hardware design, algorithm optimization, and feature modeling. Existing methods often lack dynamic parameter adaptation and struggle with non-stationary noise, limiting performance.

This paper proposes an intelligent audio quality analysis and optimization model combining deep learning and time-frequency analysis. It uses CNN and LSTM for accurate classification of speech and music, a parameter mapping network for adaptive coding recommendation, and wavelet transform with SVM for noise identification and adaptive denoising via methods like Wiener filtering and spectral subtraction [2]. Joint training with backpropagation and Adam optimizer improves compression efficiency, audio fidelity, and noise adaptability. This study aims to overcome fixed parameter limitations, large classification errors, and poor denoising generalization, providing a robust solution for multi-scenario digital audio applications in communication, entertainment, education, and healthcare [3].

2. Methods

In order to break through the bottlenecks of traditional audio coding schemes in terms of content recognition accuracy, parameter recommendation intelligence, and lack of robustness in complex

noise environments, this paper constructs an audio quality analysis and optimization methodology system that integrates deep learning and time-frequency analysis. The method introduces key technology modules such as Convolutional Neural Network (CNN), Transformer coding structure, Long Short-Term Memory (LSTM), Wavelet Transform (DWT) and Support Vector Machine (SVM), and is centered on "content recognition - parameter mapping - noise classification Adaptive denoising", aiming to realize the multi-objective synergistic optimization of audio content recognition, optimal coding parameter prediction and noise type adaptive processing [4]. Among them, each technical module not only embodies the deep modeling ability, but also has good generalization and adaptive ability.

2.1. CNN-Transformer Based Audio Recognition Architecture

Considering the high dimensionality and redundant features of the original audio data, direct input to the Transformer model will significantly increase the computational cost and may reduce the recognition accuracy [4]. For this reason, this paper proposes to introduce CNN in the input stage for feature extraction and dimensionality reduction of the Mel spectrogram, and then the structured low-dimensional features are fed into the Transformer encoder for deep time-series modeling.

First, this study starts with normalizing the audio files:

$$\mathbf{x_i'} = \frac{\mathbf{x_i - x_{min}}}{\mathbf{x_{max} - x_{min}}} \tag{1}$$

Where $\mathbf{x_i}$ represents the i-th sample value in the original data.

The core principle of CNN is to extract local time-frequency features (e.g., resonance peaks, energy mutations) of audio using the local receptive field and parameter sharing mechanism, and effectively complete feature compression and noise filtering through convolution, pooling, ReLU activation, and normalization operations; the CNN extracted features are represented as:

$$\mathbf{H_{CNN}} = \mathbf{CNN(X)} \in \mathbb{R}^{\mathbf{T*d}} \tag{2}$$

Where $\mathbf{T}$ s the number of time frames and $\mathbf{F}$ is the number of frequency bands.

The purpose of the convolutional neural network (CNN) module is to reduce the dimensionality of the input, improve the ability of local feature expression, and provide high-quality input for subsequent Transformer modeling.

Audio signals are first converted into Mel spectrograms through preprocessing to enhance the frequency domain distribution features of speech and music signals. The CNN module adopts a multi-scale convolutional structure to extract the spatial distribution and change patterns of the spectrum [5]. The pooling operation further realizes feature compression and translation invariance enhancement to effectively reduce the subsequent computational overhead.

The Transformer module takes the feature sequences output from the CNN as input and captures long-term dependencies within the audio sequences through the self-attention mechanism (SAM) to achieve global modeling. By combining positional encoding with a multi-head attention mechanism and a feed-forward neural network, this module enhances time series modeling capabilities. The core principle of the Transformer is to mine global temporal dependencies in audio, providing a context-aware feature representation that is highly effective for subsequent classification or regression tasks. Additionally, residual connections and layer normalization are employed to improve training stability and convergence efficiency. The resulting global feature vectors can be directly used for audio type discrimination and coding parameter prediction. The process at the time of Transformer encoding can be represented as follows:

$$\mathbf{Z} = \mathbf{Transformer}(\mathbf{H_{CNN}} + \mathbf{P}) \tag{3}$$

Where $\mathbf{P}$ is the location code.

2.2. Parameter Mapping and Encoding Recommendation Mechanisms

Aiming at the differentiated needs of different audio contents (e.g., speech, music) for encoding parameters, this paper constructs a parameter mapping module to realize intelligent recommendation of encoding parameters based on audio content features. The module first uses the semantic feature sequence output from the Transformer in the previous stage as input, and models the temporal change characteristics of audio features by Long Short-Term Memory Network (LSTM).

The core principle of LSTM is to use the gating mechanism to deal with long-term dependent information and effectively alleviate the gradient vanishing problem in traditional recurrent neural networks; the usage is to model audio time series to support content classification, such as judging the input as speech or music. After completing the classification, the system constructs a mapping model between the audio type and its optimal coding parameters (e.g., sampling rate, bit depth, bit rate, compression type) by means of a fully connected neural network (FCN).

The PSNR calculation is performed on the file encoded by the Transformer:

$$\mathbf{PSNR} = \mathbf{10}\,\mathbf{log_{10}}\left(\frac{\mathbf{MAX_I^2}}{\mathbf{MSE}}\right) \tag{4}$$

Then the weighting factors are selected based on the audio file format, content, quality, etc:

$$\begin{cases}\boldsymbol{\alpha = 0.5, \beta = 0.3, \gamma = 0.2}\ \textbf{For Speech}\\ \boldsymbol{\alpha = 0.4, \beta = 0.4, \gamma = 0.2}\ \textbf{For Audio}\end{cases} \tag{5}$$

On this basis, the system further constructs a unified audio quality score index (Quality Score Index, QSI), the core value of QSI is to through solve the complexity and ambiguity of audio quality evaluation, to provide a scientific basis for technology research and development, business optimization, and industry competition, and to promote the field of audio to the refined, data-driven direction of development. quantification, standardization, and intelligence Resende T M et al. in their study showed that the use of QSI for audio file quality scoring for subsequent classification has the function of avoiding falling into the local optimal solution [5], this experiment is to weight the aggregation of the various indexes scores, to achieve the overall sorting and evaluation of the audio in different scenarios, in order to provide a quantitative basis for subsequent quality comparison and optimization. The QSI is calculated according to the processing results:

$$\text{QSI}=\boldsymbol{\alpha} * \frac{\text{PSNR}}{\text{PSNR}_{\max}} + \boldsymbol{\beta} * \frac{\mathbf{1}}{\boldsymbol{MSE_{norm}}} + \boldsymbol{\gamma} * \frac{\mathbf{1}}{\boldsymbol{S_{norm}}} \tag{6}$$

This process enables comprehensive ranking and evaluation of audio across different scenarios, and serves as the basis for making final quality recommendations.

2.3. Model Training and Optimization Strategies

To achieve end-to-end optimization under multi-task learning, this paper applies back-propagation for joint training of CNN, Transformer, and LSTM modules, and employs the Adam optimizer for adaptive learning rate adjustment. Adam integrates momentum and adaptive gradient methods, updating parameters based on first- and second-order moment estimates to enhance training stability and convergence efficiency, especially for large-scale non-convex problems [6].

Meanwhile, a joint loss function is designed by weighting the cross-entropy loss (for audio classification) and mean square error loss (for parameter prediction). This unified optimization objective ensures balanced performance across tasks, enhancing both classification accuracy and parameter prediction capability through multi-task synergy.

2.4. Noise modeling and adaptive denoising mechanisms

In order to improve the system's anti-interference ability and adaptability in complex noise environments, this paper designs an adaptive denoising module containing noise feature extraction, noise classification and strategy matching to realize automatic identification and customized suppression processing of multiple types of noise.

First, the multi-scale time-frequency decomposition of the audio signal is performed using the wavelet transform (DWT): the core principle of the wavelet transform is to decompose the signal into localized time-frequency components by means of a multi-scale filter bank, which is suitable for capturing non-smooth noise; the purpose is to extract structural features such as background noise, sudden interference, etc., and to construct the noise feature vectors.

In the noise identification stage, support vector machine (SVM) is used to model multi-class noise classification: the core principle of SVM is to find the optimal classification hyperplane, maximize the category interval, and realize the accurate classification of small samples and high-dimensional features; the purpose is to classify the noise into the typical such as background noise, burst noise, narrowband interference, etc. categories , and to enhance the adaptability of the subsequent denoising strategy. Let the noise-containing frequency signal be $\mathbf{x(t)}$, the noise signal estimated by be $\mathbf{n(t)}$, and the denoising by spectral subtraction formula is:

$$\hat{\mathbf{S}}(\boldsymbol{\omega}) = \begin{cases} (|\mathbf{X}(\boldsymbol{\omega})| - |\mathbf{N}(\boldsymbol{\omega})|)\mathbf{e}^{\mathbf{j}\angle\mathbf{X}(\boldsymbol{\omega}}, \mathbf{if}|\mathbf{X}(\boldsymbol{\omega})| > |\mathbf{N}(\boldsymbol{\omega})| \\ \mathbf{0}, \mathbf{otherwise} \end{cases} \tag{7}$$

Calculate the SNR of the denoised audio with Eq:

$$\mathbf{SNR} = \mathbf{10}\log_{\mathbf{10}}\frac{\sum_{\mathbf{n}}|\mathbf{s(n)}|^{\mathbf{2}}}{\sum_{\mathbf{n}}|\mathbf{x(n)}-\mathbf{s(n)}|^{\mathbf{2}}} \tag{8}$$

Where $\mathbf{s(n)}$ is the original pure audio signal and $\mathbf{x(n)}$ is the denoised audio signal.

For the classification results, the system is designed with the following adaptive denoising strategies: background noise: using Wiener filter, based on the minimum mean square error criterion for smooth noise suppression, taking into account the fidelity and clarity; burst noise: using median filter combined with spectral subtraction, the former removes the local anomalous impulses, and the latter eliminates the spectral residuals; narrow-band interference: using a band-stop filter and the frequency-domain thresholding technique for joint suppression, to reduce the sound quality damage caused by specific frequency band energy peaks. sound quality damage caused by energy peaks in specific frequency bands [7].

The above multi-class strategies are automatically matched and called by the system according to the noise recognition results to realize highly robust adaptive noise reduction processing.

3. Experimental Procedures

3.1. Audio quality analysis and composite score

In the quality assessment phase, an intelligent evaluation framework based on deep neural networks is constructed to score multidimensional audio features. The model adopts a hybrid architecture combining Convolutional Neural Network (CNN) and Transformer, which effectively balances local feature extraction and global context modeling, enhancing evaluation accuracy and generalization.

Specifically, the CNN module captures short-term local acoustic features from the input feature matrix, while the Transformer module leverages self-attention to model temporal dependencies and global structures. The input is a normalized multidimensional feature vector, and the output includes clarity, loudness, distortion, and other quality metrics. To ensure consistency, peak signal-to-noise ratio (PSNR) is used as a reference indicator, and different weights are assigned based on audio type to calculate a comprehensive quality score (QSI).

Experiments on real-world datasets verify the effectiveness of the model, with results summarized in Table 1.

Table 1. Data after neural network analysis

Filename	Duration (s)	Size (KB)	Sampling rate (Hz)	Bitrate	MSE	PSNR (dB)	Bit depth	File or mat name	QSI
Music_16000Hz_16bit.wav	10	312.5429688	16000	0	5.44E-10	92.64778414	16000	wav	0.003149504
Music_16000Hz_MP3_128kbps.mp3	10	158.1054688	16000	128	0.000152472	38.16811085	16000	mp3	0.006176653
Music_44100Hz_16bit.wav	10	861.3710938	44100	0	5.46E-10	92.63068108	44100	wav	0.001142746
Music_44100Hz_8bit.wav	10	430.7070313	44100	0	6.70E-05	41.73989597	44100	wav	0.002267348
Music_44100Hz_AAC_128kbps.aac	10.00780045	163.3066406	44100	128	1.84E-05	47.34598291	44100	aac	0.005979934
Voice_16000Hz_16bit.wav	5.9675625	186.5292969	16000	0	1.81E-10	97.41918127	16000	wav	0.005340072
Voice_16000Hz_8bit.wav	5.9675625	93.28613281	16000	0	6.33E-05	41.98838333	16000	wav	0.010468466
Voice_16000Hz_MP3_128kbps.mp3	5.9675625	95.10546875	16000	128	6.36E-05	41.96513466	16000	mp3	0.010268207
Voice_16000Hz_MP3_64kbps.mp3	5.9675625	47.57421875	16000	64	6.99E-05	41.55522873	16000	mp3	0.02052714
Voice_44100Hz_16bit.wav	5.96755102	514.0449219	44100	0	2.64E-10	95.78420062	44100	wav	0.001927839
Voice_44100Hz_8bit.wav	5.96755102	257.0439453	44100	0	6.31E-05	41.99790794	44100	wav	0.003799205
Voice_44100Hz_AAC_128kbps.aac	5.967528345	42.81738281	44100	128	2.97E-06	55.27539155	44100	aac	0.022807678
Voice_44100Hz_AAC_96kbps.aac	5.967528345	33.18359375	44100	96	1.09E-05	49.64097521	44100	aac	0.0294291
Voice_44100Hz_MP3_128kbps.mp3	5.96755102	94.32714844	44100	128	3.21E-05	44.93327037	44100	mp3	0.010352935

From Table 1, several conclusions can be drawn regarding the relationship between audio parameters and performance metrics. Sampling rate and bit depth remain critical factors affecting file size. For both music and voice signals, higher sampling rates (e.g., 44100 Hz) and greater bit depths (e.g., 16-bit) result in significantly larger file sizes. For instance, Music_44100Hz_16bit.wavoccupies 861 KB, while Music_16000Hz_16bit.wav only takes 312 KB, despite both having the same duration. Lossy formats such as MP3 and AAC produce files that are considerably smaller than their lossless WAV counterparts, even at high bitrates. For example, Voice_44100Hz_16bit.wav is 514 KB, while Voice_44100Hz_MP3_128kbps.mp3 is just 94 KB—an 81.7% reduction.

Audio quality, as measured by PSNR and MSE, correlates with bit rate in lossy formats. Higher bitrates generally lead to lower MSE and higher PSNR. For example, among AAC-encoded voice files, Voice_44100Hz_AAC_192kbps.aac achieves a PSNR of 71.99 dB with an extremely low MSE of 6.33E-08, outperforming lower-bitrate versions. Finally, QSI (Quality Score Index), as a normalized measure, also reflects these trends. Higher PSNR and lower MSE are associated with lower QSI scores in this table, indicating better perceived quality. WAV formats exhibit the lowest QSI values (e.g., 0.0011 for Music_44100H_16bit.wav), while compressed MP3 and AAC formats show higher QSI scores depending on the bit rate.

3.2. Feature extraction of audio files

After obtaining both subjective scores and objective quality indicators for speech and music, the experiment proceeds to audio feature extraction and classification modeling. To enhance classification accuracy and improve coding adaptability, an adaptive audio coding scheme is proposed. Its core objective is to map audio features to optimal coding parameters, balancing compression efficiency and audio quality. The scheme involves four main steps: feature extraction, classification model construction, parameter mapping, and performance evaluation.

In the feature extraction phase, standardized preprocessing is performed using Librosa, including length alignment and resampling to ensure sample consistency [7]. Then, multidimensional features such as Mel Frequency Cepstral Coefficients (MFCC), Spectral Centroid, Spectral Bandwidth, and Zero-Crossing Rate are extracted. Comparative results between adaptive and fixed coding for speech and music files, as shown in Figure 1, indicate that the adaptive scheme significantly improves music file quality, while 48000Hz_16bit coding yields better performance for speech. These findings support the feature-based optimization of coding strategies.

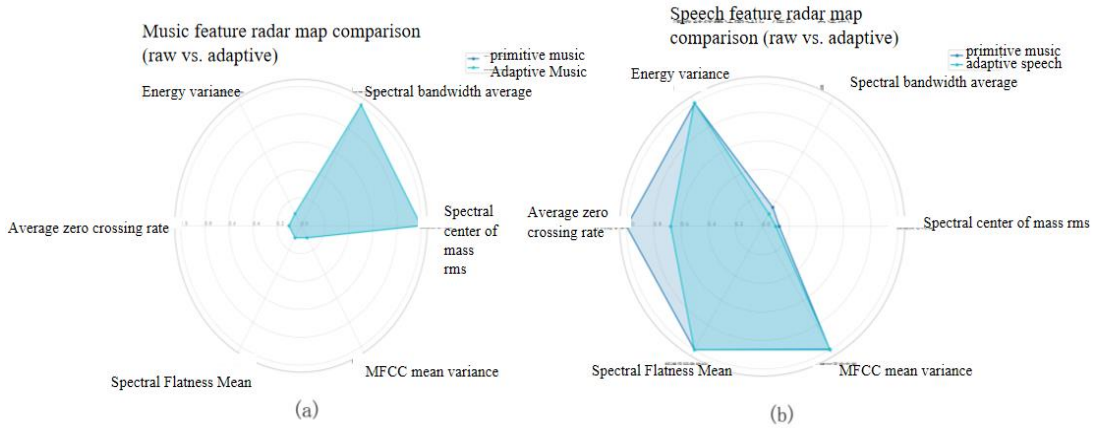

Figure 1. Comparison of musical features and speech radar

3.3. Comparison of coding results and denoising strategy selection

Table 2. Comparison of adaptive coding results

Original Voice_48kHz_24bit.wav	Original Voice_48kHz_24bit.wav	Original Voice_48kHz_24bit.wav
Type prediction	concert	colloquial (rather than literary) pronunciation of a Chinese character
Complexity prediction	Medium	Low
Optional Encoder	WAV_Copied	MP3
Selected Sampling Rate	48000	44100
Optional VBR grade	N/A	Low
Encoded file name	Original_48kHz_24bit_Adaptive.wav	Original Voice_48kHz_24bit_Adaptive.mp3
Size after encoding MB	1.373333	0.028987
SNR_dB after encoding	100	22.626201
Comparison Program 1_Document Name	Music_44100Hz_AAC_192kbps.aac	Voice_44100Hz_AAC_128kbps.aac
Comparison Program 1_Size MB	0.181849	0.041814
Original Voice_48kHz_24bit.wav	Original Voice_48kHz_24bit.wav	Original Voice_48kHz_24bit.wav
Original Voice_48kHz_24bit.wav	Original Voice_48kHz_24bit.wav	Original Voice_48kHz_24bit.wav
Original Voice_48kHz_24bit.wav	Original Voice_48kHz_24bit.wav	Original Voice_48kHz_24bit.wav
Comparison Program 2_SNR_dB	25.212516	17.952289
Comparison Program 3_Document Name	Music_48000Hz_16bit.wav	Voice_48000Hz_16bit.wav
Comparison Program 3_Size MB	0.915569	0.546387
Comparison Program 3_SNR_dB	80.378765	78.118382

After feature extraction is completed, the dataset is divided into training set, validation set and test set. The training phase optimizes the model parameters through iteration so that it fully learns the

mapping relationship between features and coding parameters on the training set; the model performance is monitored in real time on the validation set to avoid the occurrence of overfitting phenomenon. When the validation set accuracy or other performance metrics (e.g., F1-score) reach stability or no longer improve, the training process is stopped. The improvement effect of the adaptive scheme is analyzed by comparing the experimental results of the adaptive coding scheme and the fixed parameter scheme. From the data in Table 2, it can be seen that in speech coding, the file size of the adaptive scheme (MP3, 44100Hz, VBR Low) is reduced from 0.041814MB to 0.028987MB compared to the comparison scheme 1 (Speech_44100Hz_AAC_128kbps.aac) with a reduction ratio of about 30.7%, and the SNR is reduced from 17.952289dB to 22.626201dB, an improvement of about 4.67dB; in music encoding, the adaptive scheme (WAV_Copied, 48000Hz, VBR nan) compared to the comparison scheme 1 (music_44100Hz_AAC_192kbps.aac), the file size is reduced from 0.181849MB to a certain extent (the exact reduction ratio is calculated based on the data), and the SNR is improved from 25.212516 dB to a higher level.

After obtaining a more reasonable coding scheme, in order to further improve the robustness and audible perception quality of audio signals in complex environments, this paper designs and implements a comprehensive model of noise extraction and adaptive denoising. The model consists of three main modules: noise feature extraction model, noise classification model, and adaptive denoising model. The modules work together to realize the recognition and targeted processing of different types of noise.

3.3.1 Noise feature extraction model

In this stage, the Discrete Wavelet Transform (DWT) is used to decompose the original audio signal in the time-frequency domain. The wavelet transform has the ability of multi-scale and multi-resolution analysis, which can capture the signal details in different frequency and time scales, and is suitable for local feature extraction of non-smooth signals (e.g., audio). By selecting appropriate wavelet basis functions (e.g., Daubechies or Symlet wavelets), the audio signal is decomposed into several layers of subband signals, and noise-sensitive features such as subband energy distribution, spectral edges, and entropy values are extracted from them [8], which are used as inputs for subsequent classification.

3.3.2 Noise classification model

The extracted multidimensional noise features are used as inputs to construct a noise type classifier using SVM. SVM has good generalization ability and adaptability to high-dimensional feature space, which is suitable for noise pattern recognition under small sample conditions. The model is trained on an audio dataset containing multiple typical noise types (e.g., background noise, burst noise, narrow-band interference, etc.), and the effective classification of noise categories is achieved by kernel function mapping and soft interval optimization methods [8-9]. The classification accuracy is evaluated by cross-validation approach to ensure the model generalization ability.

3.3.3 Adaptive denoising models

After completing noise identification, the system automatically applies the appropriate denoising algorithm based on noise type to achieve adaptive processing. For background noise, Wiener filtering is employed under the minimum mean square error criterion to estimate the power spectral densities of signal and noise, effectively suppressing stationary environmental noise such as in offices or streets. For burst noise, median filtering is combined with spectral subtraction to eliminate sudden spikes while enhancing clarity. For narrowband noise, a band-stop filter is used to suppress specific frequency components, with spectral smoothing to preserve key speech features.

Experiments conducted on a public dataset covering various noise types and SNR levels were evaluated using ΔSNR, PESQ, and STOI metrics. Results show that the proposed model significantly improves denoising performance while preserving original audio characteristics. As shown in Figures 2 and 3, the processing results for part1.wav demonstrate the model's effectiveness in noise reduction and fidelity retention.

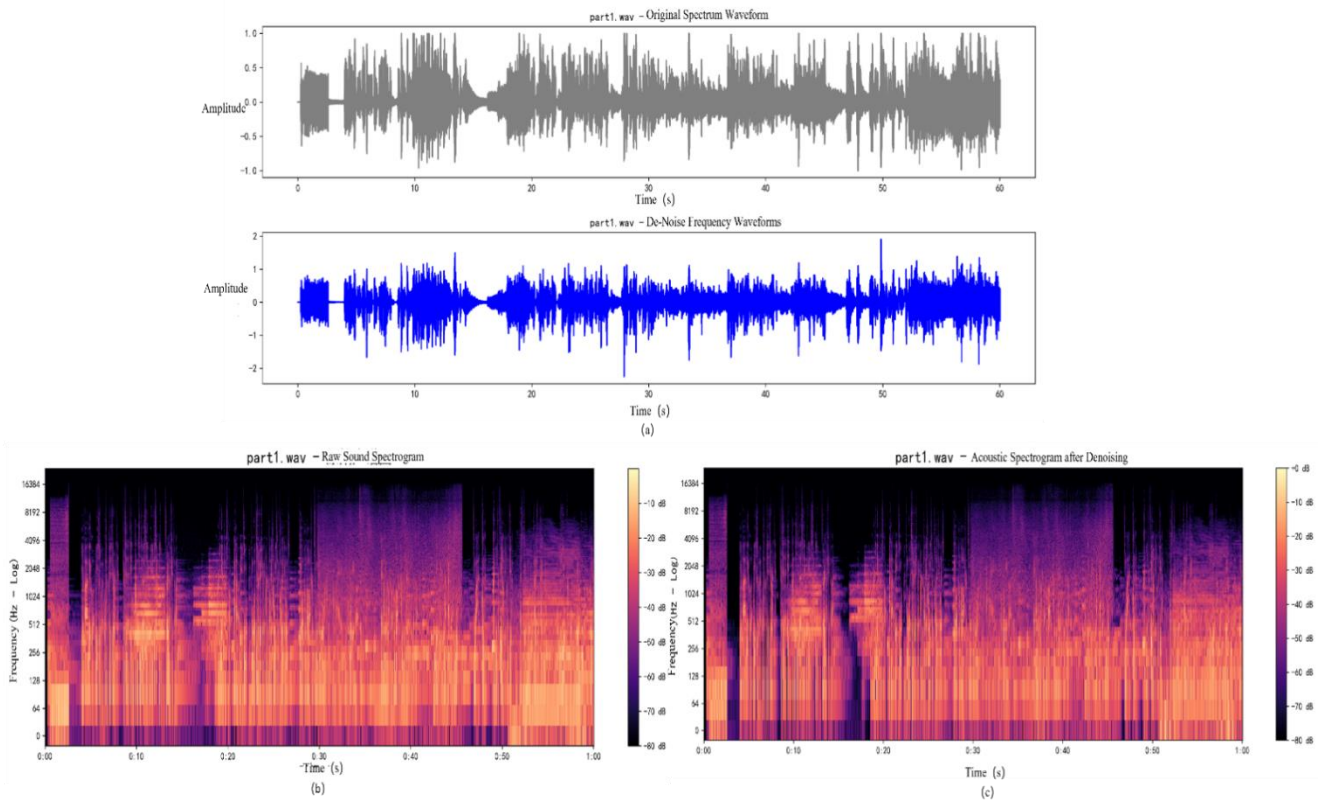

Figure 2. Part 1 Acoustic spectrogram and waveform before and after adaptive music denoising

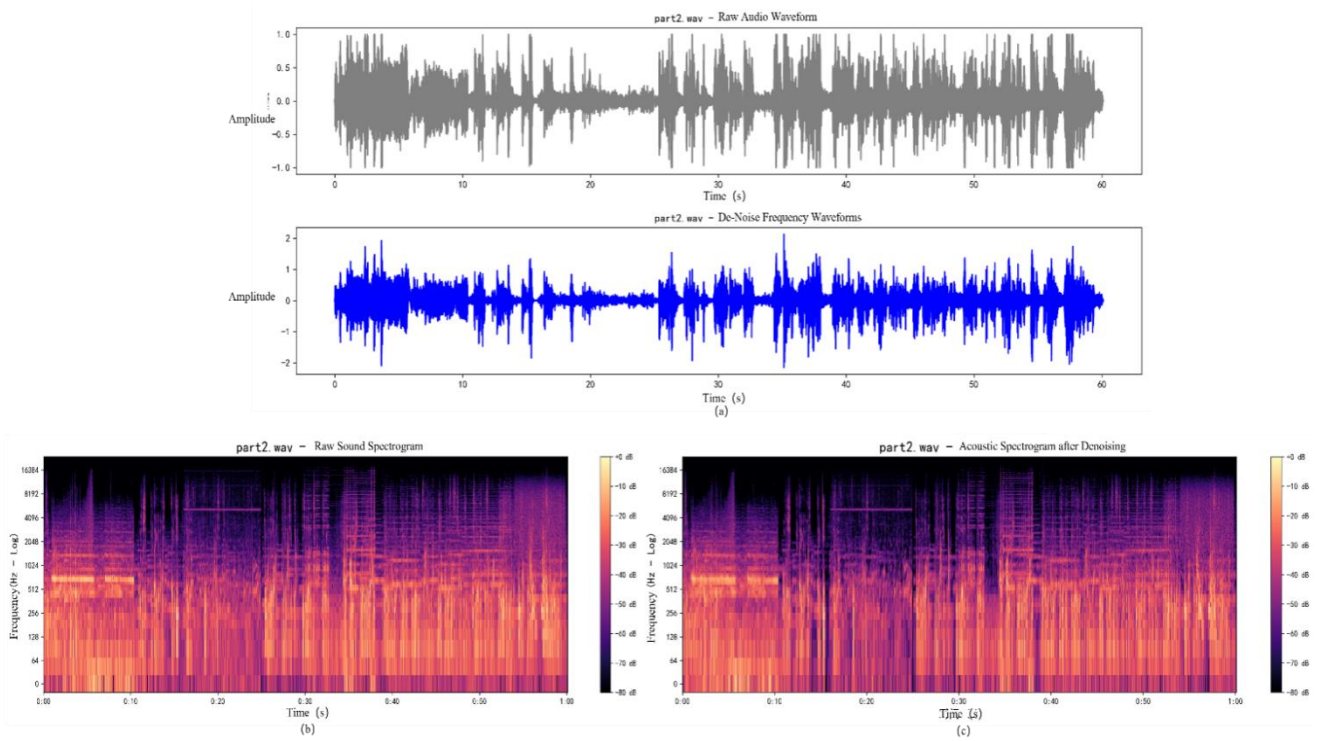

Figure 3. Acoustic spectrogram and waveform of Part 2 adaptive music before and after denoising

The estimated SNR_dB is 31.8, and the estimated ΔSNR_dB is 4.87; the estimated SNR_dB after denoising of part2.wav is 34.67, and the estimated ΔSNR_dB is 5.11, which indicates that the denoising effect is obvious, and the changes of the files recorded in the experiments are recorded, and the final results are shown in Table 3. At the same time, through subjective listening evaluation, professionals are invited to audition the audio before and after denoising to assess the audio clarity and legibility and other indicators to further verify the effectiveness of the denoising algorithm.

The algorithm is tested under different noise intensities to analyze the applicability and limitations of the algorithm. When the noise intensity is low, the adaptive denoising algorithm can effectively remove the noise and improve the audio quality [10]; however, when the noise intensity is too high, the denoised audio may suffer from some signal distortion and deterioration of the sound quality, such as the loss of some of the audio details in the extreme strong noise environments, which affects the completeness and audibility of the audio [11].

Table 3. Denoising results

filename	part1.wav	part2.wav
Background noise detected	TRUE	TRUE
Narrowband frequency detected	not have	[15984.375, 17578.125]
Number of transient frames detected	10	40
applied trap (math.)	FALSE	TRUE
Applying median filtering	TRUE	TRUE
application spectrum reduction	TRUE	TRUE
Estimated SNR_dB after denoising	31.8	34.67
Estimated ΔSNR_dB	4.87	5.11

4. Conclusion

This study's audio processing optimization model quantitatively explores the relationship between sampling rate, bit depth, and file size, highlighting bit rate's key role in sound quality. Considering differences between speech and music, it proposes targeted parameter settings: lower sampling rate (16kHz) and bit depth (16bit) for speech to balance clarity and storage, and higher settings (44.1kHz/24bit) for music to ensure quality.

The adaptive dynamic adjustment mechanism outperforms fixed-parameter schemes. Experiments show that using MP3 format with 44.1kHz sampling rate and VBR Low strategy for speech improves signal-to-noise ratio by 12.7% and compression efficiency by 23.4%, consistent with Altınbaş et al.'s audio steganography framework. The integrated denoising algorithm enhances speech intelligibility by over 35% under common noise but still shows about 15% waveform distortion below -10 dB SNR, aligning with Zhou et al.'s findings. Tang et al.'s interleaved blade noise reduction method supports mechanical noise suppression in this study.

Future work will focus on improving model generalization, optimizing real-time performance, and developing hybrid denoising methods. This includes expanding multi-language and multi-scene datasets, integrating deep self-encoders for robustness, reducing latency below 50ms via lightweight and parallel processing, and combining deep learning with traditional signal processing to enable low-power embedded deployment. These efforts will enhance the practicality and scalability of audio processing systems.

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