

WAVTOKENIZER: AN EFFICIENT ACOUSTIC DISCRETE CODEC TOKENIZER FOR AUDIO LANGUAGE MODELING

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ABSTRACT

Language models have been effectively applied to modeling natural signals, such as images, video, speech, and audio. A crucial component of these models is the codec tokenizer, which compresses high-dimensional natural signals into lower-dimensional discrete tokens. In this paper, we introduce WavTokenizer, which offers several advantages over previous SOTA acoustic codec models in the audio domain: 1) **extreme compression.** By compressing the layers of quantizers and the temporal dimension of the discrete codec, one-second audio of 24kHz sampling rate requires only a single quantizer with 40 or 75 tokens. 2) **improved subjective quality.** Despite the reduced number of tokens, WavTokenizer achieves state-of-the-art reconstruction quality with outstanding UT-MOS scores and inherently contains richer semantic information. Specifically, we achieve these results by designing a broader VQ space, extended contextual windows, and improved attention networks, as well as introducing a powerful multi-scale discriminator and an inverse Fourier transform structure. We conducted extensive reconstruction experiments in the domains of speech, audio, and music. WavTokenizer exhibited strong performance across various objective and subjective metrics compared to state-of-the-art models. We also tested semantic information, VQ utilization, and adaptability to generative models. Comprehensive ablation studies confirm the necessity of each module in WavTokenizer. The related code, demos, and pre-trained models are available at <https://github.com/jishengpeng/WavTokenizer>.

1 INTRODUCTION

In recent times, significant achievements have been made by large-scale language models (Brown et al., 2020) in generative tasks involving such as multiple-speaker speech syntheses (Wang et al., 2023; Kharitonov et al., 2023; Jiang et al., 2023b; 2024; Ji et al., 2024c), music generation (Agostinelli et al., 2023), and audio generation (Kreuk et al., 2022). Furthermore, the integration of the speech modality into multimodal unified large models also has garnered significant attention, exemplified by models such as SpeechGPT(Zhang et al., 2023a), AnyGPT(Zhan et al., 2024), GPT4-o. These successes can largely be attributed to the utilization of discrete acoustic codec representations produced by neural codec models (Zeghidour et al., 2021; Défossez et al., 2022; Kumar et al., 2023). These discrete acoustic codec models bridge the gap between continuous speech and token-based language models. It involves discretizing high-rate audio signals into a finite set of tokens, enabling the application of LLM architectures to audio data.

Most end-to-end discrete codec models (Défossez et al., 2022; Wu et al., 2023) typically adopt a three-stage structure consisting of an encoder, a Residual Vector Quantization (RVQ) module, and a decoder. The encoder performs downsampling of the audio signal in the time domain to obtain compressed audio frames. Each compressed audio frame is then quantized by a series of quantizers, with each quantizer operating on the residual of the previous one. The number of quantizers

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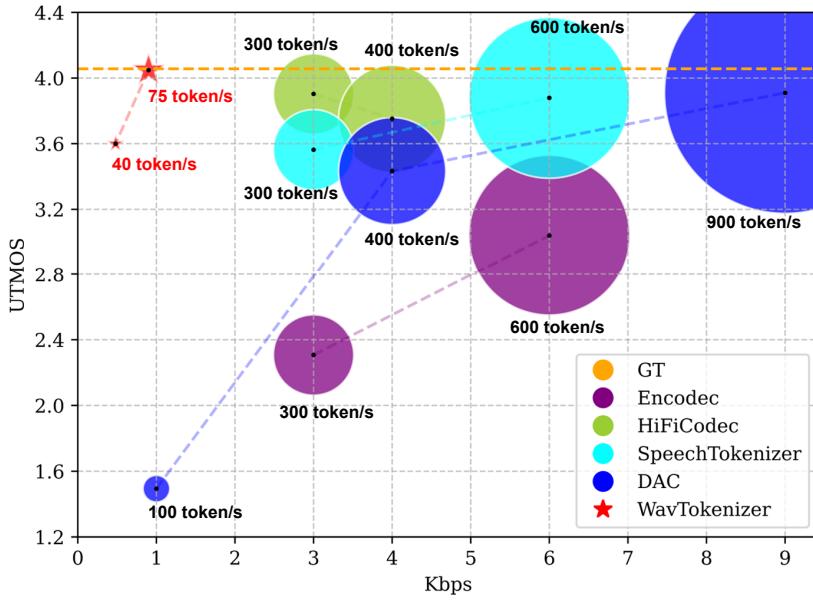


Figure 1: Comparison between WavTokenizer and state-of-the-art acoustic codec model. The vertical axis UTMOS represents reconstructed quality closer to human auditory perception, the horizontal axis kbps represents audio compression levels. The size of circles represents the number of discrete tokens per second.

determines the overall bitrate. The decoder, on the other hand, performs upsampling in the time domain to reconstruct the audio signal from the quantizer outputs. The current acoustic codec models (Kumar et al., 2023) already exhibit commendable reconstruction quality. However, there remains significant potential for exploration in areas such as high bitrate compression and semantic richness. In general, modern acoustic codec models aim to achieve the following goals:

Unified Modeling of Various Audio Signals. Compared to semantic tokens(Hsu et al., 2021; Li et al., 2023; Ma et al., 2023), acoustic tokens offer the advantage of a reconstruction paradigm that can uniformly model speech, music, and audio.

Reconstruction Quality. Current acoustic codec models have achieved human-level reconstruction quality (Kumar et al., 2023), validated in downstream generative models(Lyth & King, 2024; Jiang et al., 2023a; Ji et al., 2024d; Chen et al., 2024; SpeechTeam, 2024).

Compression. The compression level of current codec models still warrants exploration. Specifically, two aspects merit optimization: the number of quantizers and the temporal dimension of the codec. While some efforts have reduced the quantity of quantizers from eight to four(Yang et al., 2023; Ji et al., 2024a), we argue that a single quantizer layer fundamentally differs from multiple quantizers. When the number of quantizers exceeds one, downstream models require additional design efforts, such as Valle’s (Wang et al., 2023) AR and NAR structures, SoundStorm’s (Borsos et al., 2023; Ji et al., 2024b) parallel generation, MusicGen’s (Copet et al., 2024; Peng et al., 2024) slanted autoregressive structure, and UniAudio’s (Yang et al., a) global and local attention structures. With a single quantizer, speech modalities can be directly autoregressively embedded into large multimodal models(Touvron et al., 2023). Additionally, the temporal dimension of codecs, such as DAC’s (Kumar et al., 2023) requirement of 900 tokens per second, impacts both language model generation quality and resource consumption.

End-to-End Structure. Current mainstream speech representations are divided into semantic and acoustic tokens. Semantic tokens often lack acoustic information, necessitating multi-stage cascades in downstream models (Huang et al., 2024b; Anastassiou et al., 2024) to generate raw waveforms. Some codec models (Liu et al., 2024) incorporate rich semantic information but disrupt the original codec structure, requiring separate training. A robust acoustic tokenizer should at least maintain the

encoder-VQ-decoder structure. This indicates that the Codec model should primarily function as a Tokenizer and De-Tokenizer.

Rich Semantic Information. Considering the gap between the codec’s reconstruction paradigm and the generative paradigm of downstream models (SpeechTeam, 2024; Chu et al., 2024), more semantic information can facilitate weakly supervised text-to-speech generation. While many approaches attempt to introduce semantic information, additional pre-trained semantic modules (Zhang et al., 2023b) can interfere with the unified modeling of music and audio. Exploring more elegant ways to integrate semantic information directly into the codec remains an open question.

Compared to other acoustic codec models, in this paper, we introduce WavTokenizer, **a discrete acoustic codec model that meets all the aforementioned criteria for the first time** and achieves breakthroughs in **compression, reconstruction quality, and semantic modeling**. Specifically, by employing a multi-scale discriminator and an inverse Fourier transform upsampling structure from the vocoder to the decoder, WavTokenizer enhances audio reconstruction quality. To compress the codec from multiple quantizers to a single one, we discovered that simply expanding the VQ space, alongside recent K-means clustering initialization and random awakening strategies, can significantly compress audio representations while maintaining high codebook utilization. Additionally, expanding the contextual window for speech modeling and incorporating attention networks in the decoder not only balances reconstruction quality and compression but also enriches the model’s semantic information. Our main contributions are summarized as follows:

- **Conceptual Contribution.** We introduce the concept of compressing the quantizer layers of acoustic codec models to a single quantizer and enhance semantic information without disrupting the codec paradigm for modeling music and audio. With a detailed analysis of the codebook space in section 3.2, we propose aligning the speech space with the textual vocabulary, suggesting its potential as a latent form of a unique language.
- **Technical Contribution.** Utilizing K-means clustering initialization and random awakening strategies on the VQ codebook space, we designed an expanded VQ space, compressing the codec model to a single quantizer. Furthermore, we designed extended contextual modeling windows and added attention mechanisms in the decoder. The integration of an inverse Fourier transform module and multi-scale discriminator in the vocoder also aids in improved reconstruction.
- **Experimental Contribution.** WavTokenizer surpasses the current state-of-the-art models’ subjective reconstruction performance with only 75 tokens per second. It achieves comparable results with 40 or 75 tokens per second across broader metrics. Additionally, we tested WavTokenizer’s semantic information, codebook utilization, and performance in generative models, outperforming baselines. Rigorous ablation studies confirm the necessity of each component in WavTokenizer.¹

2 RELATED WORK

2.1 ACOUSTIC CODEC MODELS

In recent times, neural acoustic codecs (Zeghidour et al., 2021; Défossez et al., 2022; Kumar et al., 2023) have demonstrated remarkable capabilities in reconstructing high-quality audio at low bitrates. Typically, these methods employ an encoder to extract deep features in a latent space, which are subsequently quantized before being fed into the decoder. Given that acoustic tokens, compared to semantic tokens, can support audio, speech, and music domains, and their rich acoustic details can avoid the need for cascading architectures in downstream generative models(Kharitonov et al., 2023; Huang et al., 2024b) or multimodal large models(SpeechTeam, 2024; Anastassiou et al., 2024), the current optimization directions for acoustic codec models can be categorized into the following three directions:

Pursuing Better Reconstruction Quality. AudioDec (Wu et al., 2023) has demonstrated the importance of discriminators. PromptCodec (Pan et al., 2024) enhances representation capabilities

¹We will validate additional conclusions and present more experimental results in the future arXiv version and Github.

through additional input prompts. DAC (Kumar et al., 2023) significantly improves reconstruction quality through techniques like quantizer dropout and a multi-scale STFT-based discriminator. Vocos (Siuzdak, 2023) eliminates codec noise artifacts using a pre-trained Codec with an inverse Fourier transform vocoder. HILCodec (Ahn et al., 2024) introduces the MFBD discriminator to guide codec modeling. APCodec (Ahn et al., 2024) further enhances reconstruction quality by incorporating ConvNextV2 modules in the encoder and decoder.

Enhancing Compression. HiFi-Codec (Yang et al., 2023) proposes a parallel GRVQ structure, achieving good speech reconstruction with just four quantizers. Language-Codec (Ji et al., 2024a) introduces the MCRVQ mechanism to evenly distribute information across the first quantizer, also requiring only four quantizers for excellent performance across various generative models. **Concurrently**, Single-Codec (Li et al., 2024) designs additional BLSTM, hybrid sampling, and resampling modules to ensure basic performance with a single quantizer, though reconstruction quality still needs improvement.

Deepening Understanding of Codec Space. TiCodec (Ren et al., 2024) models codec space by distinguishing between time-independent and time-dependent information. FACodec (Ju et al.) further decouples codec space into content, style, and acoustic detail modules. Additionally, recognizing the importance of semantic information in generative models, recent efforts have begun integrating semantic information into codec models. RepCodec (Huang et al., 2024c) learns a vector quantization codebook by reconstructing speech representations from speech encoders like HuBERT or Data2vec (Baevski et al., 2022). SpeechTokenizer (Zhang et al., 2023b) enriches the semantic content of the first quantizer through semantic distillation. FunCodec (Du et al., 2023) makes semantic tokens optional and explores different combinations. SemanticCodec (Liu et al., 2024) which is based on quantized semantic tokens, further reconstructs acoustic information using an audio encoder and diffusion model.

Compared to the aforementioned approaches, WavTokenizer achieves impressive reconstruction results with only one quantizer and through 40 or 75 tokens. In contrast, for one second of audio, DAC (Kumar et al., 2023) requires 900 tokens and models with 9 quantizers. Furthermore, incorporating semantic information within the codec can constrain its modeling capabilities for music and audio. WavTokenizer explores the possibility of enhancing semantic information by strengthening the capabilities of the Codec itself.

3 WAVTOKENIZER

Our model is built on the framework of VQ-GANs, following the same pattern as SoundStream (Zeghidour et al., 2021) and EnCodec (Défossez et al., 2022). Specifically, WavTokenizer passes the raw audio X through three modules. 1) a full convolution encoder network that takes the input audio and generates a latent feature representation Z ; 2) A single quantizer discretizes Z to generate a discrete representation Z_q . 3) an improved decoder that reconstructs the audio signal \hat{X} from the compressed latent representation Z_q . The model is trained end-to-end, optimizing a reconstruction loss applied over both time and frequency domains, along with a perceptual loss in the form of discriminators operating at different resolutions.

Considering that WavTokenizer is designed as a discrete token representation for large audio language models, the focus should be on the subjective reconstruction quality of the codec (audio fidelity) and semantic content information. In Figure 1, we visualize the relationship between bitrates and UTMOS metrics (Saeki et al., 2022) across different codec models. We can observe that WavTokenizer achieves state-of-the-art reconstruction quality with only 75 tokens. Additionally, it explores extreme compression bitrates, achieving a UTMOS score of 3.6 at 0.48 kbps.

3.1 ENCODER

Follow Encodec (Défossez et al., 2022), the encoder model consists of a 1D convolution with C channels and a kernel size of 7 followed by B convolution blocks. Each convolution block is composed of a single residual unit followed by a down-sampling layer consisting of a stridden convolution, with a kernel size of twice the stride S. The residual unit contains two convolutions with kernel size 3 and a skip-connection. The number of channels is doubled whenever down-sampling occurs. The convolution blocks are followed by a two-layer LSTM for sequence modeling and a final 1D

convolution layer with a kernel size of 7 and D output channels. Following Encodenc, we use C = 32, B = 4, D=512, and use ELU (Clevert et al., 2015) as a non- linear activation function. For Stride S, we employed two configurations, (2, 4, 5, 8) and (4, 5, 5, 6), to ensure that WavTokenizer can downsample 24 kHz speech by factors of 320 and 600 along the time dimension.

3.2 RETHINKING VECTOR QUANTIZATION SPACE

The goal of WavTokenizer is to compress speech representations into the codebook space of a single quantizer. This allows for the seamless serialization of speech, avoiding the need for hierarchical design in downstream models across channel dimensions (Wang et al., 2023; Yang et al., a; Borsos et al., 2023). Initially, without changing any structure, we attempted to rely solely on a single quantizer for reconstruction during training but found the results suboptimal. Considering the vast vocabulary space in the natural language, we hypothesized that treating speech as a unique language might yield better results. Consequently, we firstly expanded the codebook space from 2^{10} to 2^{14} . We trained on 585 hours of LibriTTS and visualized the probability distribution of codebooks on the LibriTTS test-clean dataset, as shown in Figure 2 (a). We observed a concentration of the speech vocabulary space to the left of 2^{12} , indicating potential in utilizing a larger 2^{12} speech vocabulary space. Current codec codebooks 2^{10} may not fully exploit the potential of speech space.

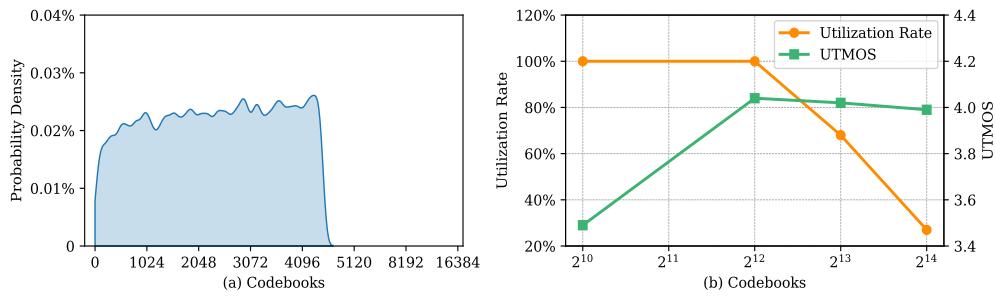


Figure 2: The visualization analysis of the WavTokenizer’s quantized codebook space. Figure (a) illustrates the probability distribution of each codebook index (1-16384) across the LibriTTS test-clean set. Figure (b) examines the relationship between reconstruction quality and codebook utilization across different codebook spaces.

Furthermore, expanding the quantized codebook space could lead to lower utilization rates. Leveraging recent advancements in codec models (Défossez et al., 2022; Ju et al.), we used k-means clustering to initialize the codebook vectors. We adjusted the number of cluster centers to 200 to align with the larger codebook space. During training, each input’s selected code is updated using an exponential moving average with a decay of 0.99, and codes unassigned for several batches are replaced with input vectors randomly sampled from the current batch. This forced activation strategy (Dhariwal et al., 2020) helps ensure effective utilization of the large codebook space. As shown in Figure 2 (b), we analyzed the relationship between codebook utilization rate and reconstruction result, confirming that 2^{12} is appropriate, consistent with the conclusions from Figure 2 (a), expanding the corresponding codebook space appropriately can reduce information loss caused by compressing the hierarchical RVQ structure into a single quantizer. Speech can be effectively reconstructed under a serialized quantizer structure, with a codebook space of 2^{12} achieving a favorable balance between utilization and reconstruction quality. This suggests the potential for aligning speech with a broad natural language vocabulary, forcefully mapping it through the tokenizer as a unique language. We will verify this in subsequent experiments.

3.3 IMPROVED DECODER

As in FACodec (Ju et al.), we believe that the decoder plays a more crucial role than the encoder during the acoustic codec reconstruction process. Upsampling and reconstructing from the highly compressed information in WavTokenizer is particularly challenging.

WavTokenizer does not employ a mirrored decoder upsampling structure. This standard practice (Kumar et al., 2023) involves using a stack of dilated convolutions to increase the receptive field, and

transposed convolutions to sequentially upsample the feature sequence to the waveform. However, this design is known to be susceptible to aliasing artifacts instead. Following Vocos (Siuzdak, 2023), we maintain consistent feature resolution at all depths, achieving waveform upsampling through inverse Fourier transform. In the decoder section, the target audio signal \tilde{X} is represented using Short-Time Fourier Transform (STFT):

$$STFT(\tilde{X}_{[m,k]}) = \sum_{n=0}^N \tilde{X}[n] w[n-m] e^{-j2\pi kn/K} \quad (1)$$

Here, K represents the number of frequency points after performing the Discrete Fourier Transform (DFT), while k denotes the frequency index. N corresponds to the number of points in the sampled sequence, with n representing a particular sample point, and m indicating the index length. In the practical implementation, the Short-Time Fourier Transform (STFT) is performed by applying a series of Fast Fourier Transforms (FFTs) to overlapping and windowed frames of data. The window function advances or hops through time to create these frames.

Moreover, to directly enhance the semantic modeling capability of the acoustic codec model, rather than adding various semantic tokens (Zhang et al., 2023b), we introduced an attention module (Rombach et al., 2022) in the decoder. Although attention models have proven their scalability and high performance in broader tasks (Dosovitskiy et al., 2020; Fang et al., 2024; Huang et al., 2024a; Yang et al., b), the encoder-decoder structure in the acoustic codec model remains fully convolutional. Concerns may arise about the potential extrapolation issues of attention models when modeling long sequences during inference, given that acoustic codec models often train on randomly selected one-second audio clips. However, our experiments show that WavTokenizer achieves good reconstruction even for long audio sequences during inference. Incorporating an attention network module into the decoder can enhance information reconstruction and semantic modeling. Additionally, we discovered a simple trick, expanding contextual modeling windows to three seconds for WavTokenizer with attention modules will further improve codec reconstruction during training. This is likely because one-second clips, including silence, may contain insufficient semantic information. Increasing the contextual modeling window size helps the Codec model better capture context. We validated these findings through detailed ablation studies. During our experiments, we also found that introducing an attention module in the WavTokenizer is beneficial only in the decoder. We tested various configurations within both the encoder and decoder and currently, adding the attention module before the ConvNext module appears to be the optimal solution.

Therefore, for the representation of the intermediate signals Z_q after quantization, WavTokenizer only needs to input Z_q into the conv1D layer, attention block, ConvNeXt (Liu et al., 2022) blocks, which serves as the fundamental backbone. Subsequently, a Fourier transform is performed on the real-valued signals. In the ConvNeXt Block, it first embeds the input features into a hidden dimensionality and then applies a sequence of convolutional blocks. Each block is composed of a large-kernel-sized depthwise convolution, followed by an inverted bottleneck that projects features into a higher dimensionality using pointwise convolution. GELU activations (Hendrycks & Gimpel, 2016) are used within the bottleneck, and Layer Normalization is employed between the blocks. Regarding the transformation of real-valued signals, we utilize a single side band spectrum, resulting in $n_{fft}/2 + 1$ coefficients per frame. Since we parameterize the model to output both phase and magnitude values, the activations of the hidden dimensions are projected into a tensor h with $n_{fft} + 2$ channels. Finally, the inverse Fourier transform \mathcal{F}^{-1} can be used to reconstruct the final audio directly.

3.4 SUPERIOR DISCRIMINATOR AND LOSS FUNCTION

The adversarial loss is used to promote perceptual quality. We employ the multi-period discriminator (MPD) as defined by (Kong et al., 2020) and the multi-resolution discriminator (MRD) (Jang et al., 2021). Furthermore, to learn discriminative features about a specific sub-band and provide a stronger gradient signal to the generator, following (Kumar et al., 2023), we use a multi-scale discriminator (MSD) and a complex STFT discriminator (Zeghidour et al., 2021) at multiple time-scales (Défossez et al., 2022). We adopt a hinge loss formulation instead of the least squares GAN objective, as suggested by (Zeghidour et al., 2021). To train the discriminator, we can optimize the following

objective function $\mathcal{L}_{dis}(X, \tilde{X})$:

$$\frac{1}{K} \sum_{k=1}^K \max(0, 1 - D_k(X)) + \max(0, 1 + D_k(\tilde{X})) \quad (2)$$

The variable K represents the number of discriminators. D_k represents the k -th discriminator. Regarding the loss for the generator, the WavTokenizer model consists of four components: quantizer loss, mel-spectrum reconstruction loss, adversarial loss, and feature matching loss. The quantizer loss can be defined as follows:

$$\mathcal{L}_q(Z, Z_q) = \sum_{i=1}^N \|Z_i - \hat{Z}_i\|_2^2 \quad (3)$$

The mel-spectrum reconstruction loss can be defined as follows:

$$\mathcal{L}_{mel}(X, \tilde{X}) = \|Mel(X) - Mel(\tilde{X})\|_1 \quad (4)$$

Furthermore, we can define the adversarial loss as a hinge loss over the logits of these discriminators:

$$\mathcal{L}_{adv} = \frac{1}{K} \sum_{k=1}^K \max(0, 1 - D_k(\tilde{X})) \quad (5)$$

The feature matching loss, denoted as \mathcal{L}_{feat} , is calculated as the mean of the distances between the l th feature maps of the k th subdiscriminator:

$$\mathcal{L}_{feat} = \frac{1}{K * L} \sum_k \sum_l \|D_k^l(X) - D_k^l(\tilde{X})\|_1 \quad (6)$$

In the end, the total loss of the generator \mathcal{L}_{gen} is:

$$\mathcal{L}_{gen} = \lambda_q \mathcal{L}_q + \lambda_{mel} \mathcal{L}_{mel} + \lambda_{adv} \mathcal{L}_{adv} + \lambda_{feat} \mathcal{L}_{feat} \quad (7)$$

where $\lambda_q, \lambda_{mel}, \lambda_{adv}, \lambda_{feat}$ are the hyper-parameters to control the training objective function.

4 EXPERIMENTS

4.1 EXPERIMENTS SETUPS

Dataset To ensure unified modeling across multilingual speech, music, and audio domains, the WavTokenizer-large version was trained on approximately 80k hours of data. For the speech domain, we used LibriTTS (Zen et al., 2019), VCTK (Veaux et al., 2016), CommonVoice (Ardila et al., 2019), and LibriLight (Kahn et al., 2020). For the audio domain, we utilized AudioSet (Gemmeke et al., 2017), and for the music domain, we employed the Jamendo (Bogdanov et al., 2019) and MusicDB (Rafii et al., 2017) datasets. We evaluated codec reconstruction performance in clean and noisy environments using the LibriTTS test-clean and test-other sets, and assessed audio and music performance with the AudioSet eval and MusicDB test sets. For the WavTokenizer-medium version, a subset of the above datasets totaling around 5,000 hours was used. The WavTokenizer-small version was trained on just 585 hours of LibriTTS (Zen et al., 2019).

Baselines We selected the current state-of-the-art codec models as the baseline for WavTokenizer. To ensure a fair comparison, we employed the official weight files provided by the Encodec² (Défossez et al., 2022), HiFi-Codec³ (Yang et al., 2023), Vocos⁴ (Siuzdak, 2023), SpeechTokenizer⁵ (Zhang et al., 2023b) and DAC⁶ (Kumar et al., 2023) frameworks.

Training and Inference Settings We train WavTokenizer-small up to 1 million iterations, with 500 thousand iterations allocated to both the generator and discriminator on 16 NVIDIA A800 80G

²<https://github.com/facebookresearch/encodec>

³<https://github.com/yangdongchao/AcademicCodec>

⁴<https://github.com/gemelo-ai/vocos>

⁵<https://github.com/ZhangXInFD/SpeechTokenizer>

⁶<https://github.com/descriptinc/descript-audio-codec>

Table 1: The reconstruction results of different codec models on the LibriTTS Test-Clean dataset. Nq represents the **number of quantizers**.

Model	Bandwidth ↓	Nq ↓	token/s ↓	UTMOS ↑	PESQ ↑	STOI ↑	V/UV F1 ↑
GT	-	-	-	4.0562	-	-	-
DAC	9.0kbps	9	900	3.9097	3.9082	0.9699	0.9781
Encodec	6.0kbps	8	600	3.0399	2.7202	0.9391	0.9527
Vocos	6.0kbps	8	600	3.6954	2.8069	0.9426	0.9437
SpeechTokenizer	6.0kbps	8	600	3.8794	2.6121	0.9165	0.9495
DAC	4.0kbps	4	400	3.4329	2.7378	0.9280	0.9572
HiFi-Codec	3.0kbps	4	400	3.7529	2.9611	0.9405	0.9617
HiFi-Codec	4.0kbps	4	300	3.9035	3.0116	0.9446	0.9576
Encodec	3.0kbps	4	300	2.3070	2.0517	0.9007	0.9198
Vocos	3.0kbps	4	300	3.5390	2.4026	0.9231	0.9358
SpeechTokenizer	3.0kbps	4	300	3.5632	1.9311	0.8778	0.9273
DAC	1.0kbps	1	100	1.4940	1.2464	0.7706	0.7941
WavTokenizer-small	0.5kbps	1	40	3.6016	1.7027	0.8615	0.9173
WavTokenizer-small	0.9kbps	1	75	4.0486	2.3730	0.9139	0.9382

GPUs. Throughout the entire training process, all input speech, music, and audio samples were resampled to 24 kHz, and the batch size was 40. WavTokenizer-Large was trained for 10 days with 8 epochs in the same configuration. During the training phase, we uniformly truncated excessively long segments in the training data to a fixed length of 10 seconds and subsequently performed a random crop of the waveform to obtain audio snippets of 3-second duration for feeding WavTokenizer. WavTokenizer is optimized using the AdamW optimizer with an initial learning rate of 2e-4 and betas set to (0.9, 0.999). The learning rate was decayed based on a cosine schedule.

Automatic metrics For objective evaluation of our codec models, following the methodology proposed by Vocos (Siuzdak, 2023) to evaluate the performance of discrete codecs, we employ the UTMOS (Saeki et al., 2022) automatic Mean Opinion Score (MOS) prediction system. UTMOS can yield scores highly correlated with human evaluations and is restricted to 16 kHz sample rate. we also adopt the metrics from speech enhancement fields, such as the PESQ (Rix et al., 2001), STOI, and the F1 score for voiced/unvoiced classification (V/UV F1). To evaluate Speaker Embedding Cosine Similarity (SECS) between reconstructed audio and ground truth audio, we employ WavLM-TDNN (Chen et al., 2022).

4.2 RECONSTRUCTION RESULTS ABOUT SPEECH

We evaluated the reconstruction performance of different codec models on the LibriTTS test-clean subset, which consists of 4,837 audio samples. Notably, RVQ-based codec models often select quantizers with varying bandwidths during training. To ensure fair comparisons, we used the quantizers that the baseline models were trained on. The results are shown in Table 1, where we observe the following: 1) WavTokenizer achieved impressive results on the UTMOS metric, with the WavTokenizer-small at 0.9 kbps surpassing the state-of-the-art DAC model by 0.15. We believe the UTMOS metric closely aligns with human perception of audio quality, indicating that WavTokenizer maintains excellent reconstruction under extreme compression. 2) When compared to the current SOTA DAC model with a single quantizer, WavTokenizer with 40 and 75 tokens significantly outperformed DAC with 100 tokens across all metrics. This demonstrates that WavTokenizer is the first model capable of effectively reconstructing audio with a single quantizer. 3) On objective metrics such as STOI, PESQ, and F1 score, WavTokenizer is comparable to the Vocos model with four quantizers and the SpeechTokenizer model with eight quantizers.

To comprehensively evaluate the reconstruction performance of WavTokenizer in the field of speech, we have supplemented results on the LibriTTS Test-Other dataset and the LJSpeech dataset. These represent audio reconstruction in the noisy and out-of-domain environments, respectively. The experimental results are shown in Table 2 and Table 3. In the noisy environment, we found that WavTokenizer-small achieves similar conclusions to those findings in Table 1, demonstrating good reconstruction performance using only 75 tokens. Additionally, on the out-domain dataset in Table 3, we observed some performance degradation for WavTokenizer-small. This may be due to the training of WavTokenizer-small is on a limited dataset size.

4.3 SEMANTIC REPRESENTATION EVALUATION

We evaluate the semantic richness of different codec models on the ARCH benchmark (La Quatra et al., 2024). It is noteworthy that we opted not to utilize the conventional Superb benchmark (Yang et al., 2021) due to its exclusive focus on the speech domain, while ARCH enables further assessment of Codec models’ performance in music and audio realms. The ARCH benchmark comprises four datasets within the speech domain, namely Emotional Speech and Song (RAVDESS) (Livingstone & Russo, 2012), Audio-MNIST (AM), Spoken Language Understanding Resource Package (SLURP) (Bastianelli et al., 2020), and EMOVO dataset. We extract embeddings corresponding to the discrete codebooks of codec models as their respective representations and evaluate the classification performance of acoustic codec models on downstream datasets by inputting these representations.

The experimental results, as shown in Table 4, indicate that WavTokenizer achieves state-of-the-art classification performance when configured with a single quantizer, compared to the baseline Codec and DAC models. Remarkably, on the AM and SLURP datasets, WavTokenizer surpasses the classification performance of DAC with nine quantizers and Codec with eight quantizers. These findings suggest that WavTokenizer effectively captures rich semantic information.

Table 2: The reconstruction results of different codec models on the LibriTTS Test-Other dataset. Nq represents the **number of quantizers**. This experimental setup represents the performance about reconstructing speech in the noisy environments.

Model	Bandwidth ↓	Nq ↓	token/s ↓	UTMOS ↑	PESQ ↑	STOI ↑	V/UV F1 ↑
GT	-	-	-	3.4831	-	-	-
Codec	6.0kbps	8	600	2.6568	2.6818	0.9241	0.9338
Vocos	6.0kbps	8	600	3.1956	2.5590	0.9209	0.9202
SpeechTokenizer	6.0kbps	8	600	3.2851	2.3269	0.8811	0.9205
HiFi-Codec	4.0kbps	4	400	3.0750	2.5536	0.9126	0.9387
HiFi-Codec	3.0kbps	4	300	3.3034	2.6083	0.9166	0.9318
Codec	3.0kbps	4	300	2.0883	2.0520	0.8835	0.8926
Vocos	3.0kbps	4	300	3.0558	2.1933	0.8967	0.9051
SpeechTokenizer	3.0kbps	4	300	3.0183	1.7373	0.8371	0.8907
DAC	1.0kbps	1	100	1.4986	1.2454	0.7505	0.7775
WavTokenizer-small	0.5kbps	1	40	3.0545	1.6622	0.8336	0.8953
WavTokenizer-small	0.9kbps	1	75	3.4312	2.2614	0.8907	0.9172

Table 3: The reconstruction results of different codec models on the LJSpeech dataset. Nq represents the **number of quantizers**. This experimental setup demonstrates the effectiveness of codec models in the out-of-domain scenarios.

Model	Bandwidth ↓	Nq ↓	token/s ↓	UTMOS ↑	PESQ ↑	STOI ↑	V/UV F1 ↑
GT	-	-	-	4.3794	-	-	-
Codec	6.0kbps	8	600	3.2286	2.6633	0.9441	0.9555
Vocos	6.0kbps	8	600	4.0332	2.9258	0.9497	0.9459
SpeechTokenizer	6.0kbps	8	600	4.2373	2.6413	0.9316	0.9452
HiFi-Codec	4.0kbps	4	400	4.1656	2.7629	0.9446	0.9497
HiFi-Codec	3.0kbps	4	300	4.2692	2.9091	0.9485	0.9469
Codec	3.0kbps	4	300	2.3905	2.0194	0.9058	0.9326
Vocos	3.0kbps	4	300	3.7880	2.5006	0.9310	0.9388
SpeechTokenizer	3.0kbps	4	300	3.9908	2.0458	0.9021	0.9299
WavTokenizer-small	0.5kbps	1	40	3.6842	1.6711	0.8706	0.9189
WavTokenizer-small	0.9kbps	1	75	3.8753	1.9531	0.9007	0.9106

4.4 ABLATION EXPERIMENTS

Considering the time constraints, we conducted ablation experiments using the WavTokenizer-small model. Initially, we evaluated the impact of different codebook sizes on the performance of WavTokenizer. We recorded the frequency of each codebook entry on the LibriTTS test-clean dataset. As illustrated in Table 5 and discussed in Section 3.2, we observed significant potential for expansion in the current codebook space, even under extreme compression with a single quantizer, when combined with the latest training strategies. We found that expanding the codebook size from the typical

Table 4: The semantic representation evaluation of different codec models on the speech domain of ARCH Benchmark (La Quatra et al., 2024). Nq represents the number of quantizers.

Model	Nq ↓	token/s ↓	RAVDESS ↑	SLURP ↑	EMOVO ↑	AM ↑
DAC	9	900	0.3750	0.0779	0.2363	0.6926
Encodec	8	600	0.2881	0.0636	0.2261	0.4388
DAC	4	400	0.3194	0.0782	0.2346	0.6838
Encodec	4	300	0.2951	0.0660	0.2193	0.4301
Encodec	2	150	0.2743	0.0627	0.2193	0.3649
DAC	1	100	0.2500	0.0713	0.2278	0.6287
WavTokenizer-small	1	75	0.2951	0.0788	0.2806	0.6386

1024 to 4096 significantly enhances audio quality. For instance, UTMOS increased by 0.55, PESQ improved by 0.6, and STOI rose by 0.5. However, excessively large codebook spaces (16384) can lead to reduced vocabulary utilization.

Additionally, we explored the effect of extended contextual windows for modeling in WavTokenizer. Typically, most Codec models are trained using randomly selected one-second audio clips. However, by incorporating an attention module in WavTokenizer, we experimented with modeling longer audio segments. As shown in Table 6, we discovered that using a three-second audio contextual window further enhances the model’s reconstruction quality. We hypothesize that a one-second window may contain insufficient information and be more affected by silence. A longer contextual environment may enhance the attention module’s ability to model and extract relevant semantics.

We further investigated the impact of multi-scale STFT discriminators on reconstruction quality. As shown in Table 7, although incorporating multi-scale STFT discriminators increases training time, it can enhance the reconstruction quality of the codec model. This improvement may be due to splitting the STFT into sub-bands, which slightly improves high-frequency prediction and mitigates aliasing artifacts. The discriminator can learn discriminative features for a specific sub-band, providing a stronger gradient signal to the generator in the WavTokenizer.

Table 5: The ablation study of codebook space across different dimensions on the LibriTTS test-clean dataset, we used the WavTokenizer-small model with a single quantizer at 0.9 kbps. The utilization rate reflects the usage efficiency of the codebook.

Model	Codebooks	Utilization rate	UTMOS ↑	PESQ ↑	STOI ↑	V/UV F1 ↑
WavTokenizer-small	16384	27%	3.9989	2.3600	0.8129	0.9380
WavTokenizer-small	8192	68%	4.0220	2.3916	0.9156	0.9389
WavTokenizer-small	4096	100%	4.0486	2.3730	0.9139	0.9382
WavTokenizer-small	1024	100%	3.4967	1.7781	0.8660	0.9072

Table 6: The ablation study of different contextual modeling windows on the LibriTTS test-clean dataset, we used the WavTokenizer-small model with a single quantizer at 0.9 kbps.

Model	Codebooks	windows	UTMOS ↑	PESQ ↑	STOI ↑	V/UV F1 ↑
WavTokenizer-small	4096	1	3.7448	2.0112	0.8944	0.9203
WavTokenizer-small	4096	3	4.0486	2.3730	0.9139	0.9382
WavTokenizer-small	4096	5	4.0448	2.3556	0.9127	0.9384

4.5 MORE RESULTS

We plan to supplement additional experimental results (the speech reconstruction effects included audio and music, semantic experiments about music and audio, downstream generative experiments, more ablation experiments, and the results about WavTokenizer-medium and WavTokenizer-large) in the upcoming arXiv version.

Table 7: The ablation study of multi STFT discriminator (MSTFTD) on the LibriTTS test-clean dataset, we used the WavTokenizer-small model with a single quantizer at 0.9 kbps.

Model	UTMOS \uparrow	PESQ \uparrow	STOI \uparrow	V/UV F1 \uparrow
WavTokenizer-small w/o MSTFTD	3.7806	2.1270	0.9008	0.9269
WavTokenizer-small	4.0486	2.3730	0.9139	0.9382

5 CONCLUSION

In this paper, we introduce WavTokenizer, capable of quantizing one second of speech, music, audio into 75 or 40 high-quality tokens. Compared to existing acoustic codec models, WavTokenizer achieves comparable results on the LibriTTS test-clean dataset. We provide a detailed analysis of the design motivations for the VQ space and decoder, and validate the necessity of each new module through ablation studies. We will provide additional experimental results in the further arXiv versions.

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