

Ming-UniAudio: Speech LLM for Joint Understanding, Generation and Editing with Unified Representation

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*See Contributions section (Sec. 10) for full author list.

Existing speech models suffer from competing requirements on token representations by understanding and generation tasks. This discrepancy in representation prevents speech language models from performing instruction-based free-form editing. To solve this challenge, we introduce a novel framework that unifies speech understanding, generation, and editing. The core of our unified model is a unified continuous speech tokenizer MingTok-Audio, the first continuous tokenizer to effectively integrate semantic and acoustic features, which makes it suitable for both understanding and generation tasks. Based on this unified continuous audio tokenizer, we developed the speech language model Ming-UniAudio, which achieved a balance between generation and understanding capabilities. Ming-UniAudio sets new state-of-the-art (SOTA) records on 8 out of 12 metrics on the ContextASR benchmark. Notably, for Chinese voice cloning, it achieves a highly competitive Seed-TTS-WER of 0.95. Leveraging this foundational model, we further trained a dedicated speech editing model Ming-UniAudio-Edit, the first speech language model that enables universal, free-form speech editing guided solely by natural language instructions, handling both semantic and acoustic modifications without timestamp condition. To rigorously assess the editing capability and establish a foundation for future research, we introduce Ming-Freeform-Audio-Edit, the first comprehensive benchmark tailored for instruction-based free-form speech editing, featuring diverse scenarios and evaluation dimensions spanning semantic correctness, acoustic quality, and instruction alignment. We open-sourced the continuous audio tokenizer, the unified foundational model, and the free-form instruction-based editing model to facilitate the development of unified audio understanding, generation, and manipulation.

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Project Homepage: [Link](#)

Code: <https://github.com/inclusionAI/Ming-UniAudio>

Model: <https://huggingface.co/inclusionAI>



1 Introduction

The rapid breakthroughs in large language models (LLMs) (Brown et al., 2020; Yang et al., 2025) have significantly improved the capabilities of speech foundation models in both understanding (Chu et al., 2023; Wu et al., 2025a) and generation (Wang et al., 2023; Du et al., 2024a; Jia et al., 2025). These advances enable more accurate and fine-grained comprehension of spoken language, as well as more fluent and natural speech output for human-machine interaction (Xu et al., 2025b). In terms of speech representations, understanding and generation tasks impose fundamentally different demands: understanding benefits from compact, semantics-focused encodings, while generation requires rich, high-quality acoustic details. As a result, most existing speech language models resort to one of two architectural compromises: either maintaining separate representations for understanding and

generation (Xu et al., 2025b; KimiTeam et al., 2025), or relying on discrete tokens for both (Défossez et al., 2024; Xiaomi, 2025; Huang et al., 2025a). The former approach, separated representation, presents a fundamental challenge for editing, as the disjointed representations for understanding and generation prevent the seamless workflow required to interpret an instruction and synthesize the modified audio (Le et al., 2023). Whereas the latter approach, discrete representation, suffers from loss of speech details due to quantization. In terms of speech tasks, there is currently no single model that is capable of performing semantic and acoustic editing on input speech with free-form instructions. In contrast, multi-round editing has already been well demonstrated in the image domain, such as GPT-4o, Gemini-Image-Flash 2.5 (OpenAI, 2024; Google, 2025). To reconcile the issue of competing requirements of representations on understanding and generation tasks, we propose a VAE-based continuous audio tokenizer that unifies semantic and acoustic representation. Furthermore, we introduce a novel capability, free-form speech editing, which enables fine-grained and high-quality speech manipulation. However, building such a unified system requires addressing several fundamental challenges, which we detail in the following.

- **Inconsistent Representations: Understanding vs. Generation:** A primary hurdle lies in inconsistent representational needs for speech understanding and generation. Understanding tasks, such as automatic speech recognition (ASR) and sentiment analysis, primarily require high-level semantic information. In contrast, speech generation (e.g., text-to-speech, voice conversion) demands faithful reconstruction of fine-grained acoustic details, including prosody, timbre, and intonation. It is very challenging to reconcile their distinct requirements within a single representation, often leading to models that excel in one aspect at the expense of the other.
- **Different Training Objectives:** In the joint training of understanding and generation, there are several challenges. The optimization objectives for the two tasks are distinct, and they present different levels of training difficulty. Moreover, generation tasks typically require more training iterations. As a result, it remains a pressing problem to determine the training ratio between understanding and generation tasks to simultaneously achieve optimal performance for both tasks, especially under the multi-stage training design.
- **Limitations of Speech Editing:** Existing approaches to speech editing are generally restrictive. Many require complex, multi-stage pipelines or operate on a limited set of predefined operations (e.g., denoising, speed alteration). Expanding into more complex ‘free-form’ editing presents further challenges. Semantic content modifications (e.g., insertion, deletion, replacement) often demand timestamp conditions to specify the edit location. The lack of truly instruction-guided free-form editing capabilities limits the practical utility and accessibility of current speech editing tools.

To address these issues, we propose Ming-UniAudio, a novel framework designed to achieve unified speech understanding, generation, and free-form editing. Our key contributions are as follows.

- **Unified Continuous Speech Tokenizer:** We introduce a novel unified continuous speech tokenizer, which is built on a Variational Autoencoder (VAE) framework and implemented with a purely causal transformer architecture. This tokenizer unifies semantic and acoustic representations, optimized by multistage training and semantic distillation from an LLM. It simultaneously extracts high-dimensional unified features Z_{uni} as a universal interface for LLMs and low-dimensional acoustic latent vector Z_{latent} crucial for high-quality generation. Furthermore, this latent vector can be transformed into high-dimensional unified features via a

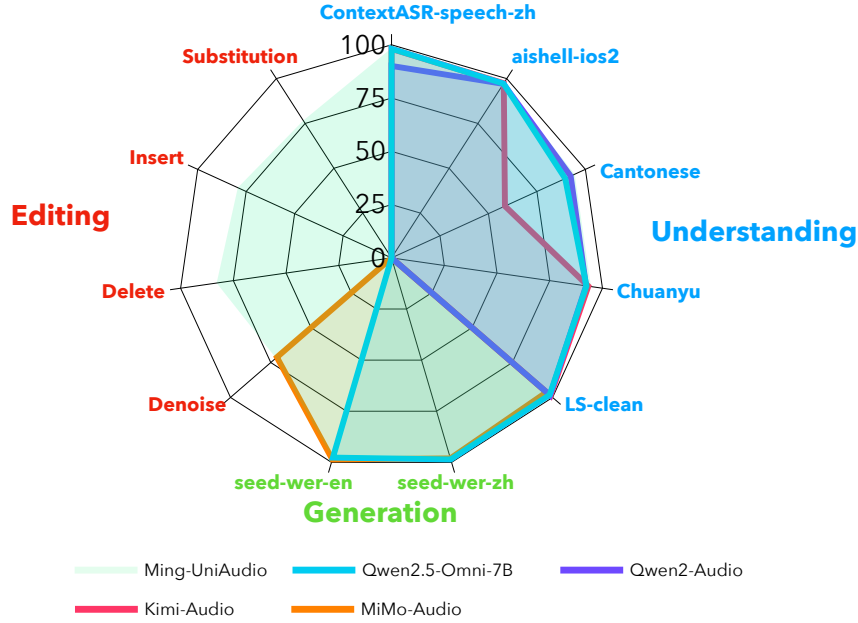


Figure 1 Comparison of Ming-UniAudio with Open-Source Speech LLMs across Understanding, Generation, and Editing Tasks.

semantic module, thereby forming a complete closed loop with the LLM’s understanding and generation tasks.

- **Unified Speech Language Model for Generation and Understanding:** We pretrained an end-to-end unified speech language model capable of both understanding and generation with a single LLM backbone. This model incorporates a per-token diffusion head that takes the LLM’s hidden states and predicted semantic sequences as conditions, ensuring high-quality and natural speech synthesis.
- **Instruction-Guided Free-Form Speech Editing:** To the best of our knowledge, this is the first work to realize a truly universal speech editing framework based entirely on free-form natural language instructions. This framework enables comprehensive editing, covering both semantic content modifications (insertion, deletion, substitution) and acoustic attribute adjustments (denoising, speed/pitch/volume, dialect/emotion conversion, etc.) without requiring the user to specify an explicit edit region. We propose Audio-Edit-Benchmark, the first open-source free-form evaluation set comprising editing tasks of three semantic and five acoustic types, to evaluate the model’s editing performance.

2 Related Work

2.1 Speech Tokenizer

Speech tokenization is crucial for representing continuous speech signals. Acoustic tokens, such as SoundStream (Zeghidour et al., 2021) or EnCodec (Défossez et al., 2022), excel at preserving high reconstruction quality but often lack rich semantic information, which can result in compromised pronunciation stability (Wang et al., 2023). Conversely, semantic tokens, such as HuBERT, Whisper,

and CosyVoice (Hsu et al., 2021; Radford et al., 2023a; Du et al., 2024b), are rich in semantic content but tend to lose acoustic details. As a consequence, a separate diffusion model is required to convert these tokens into a Mel spectrogram and inject acoustic features like timbre, prosody, and style. To address the aforementioned issues, SpeechTokenizer (Zhang et al., 2023) uses knowledge distillation to integrate semantic and acoustic features, and Step Audio Tokenizer (Huang et al., 2025a) attempts to address this by interleaving semantic and acoustic tokens. However, their discrete nature makes them suboptimal for understanding-based tasks such as speech recognition. Inspired by the work of MingTok-Vision (Huang et al., 2025b) in computer vision, we present a VAE-based continuous tokenizer with unified semantic and acoustic representation, offering greater performance than discrete approaches. This unified approach shows that a future with seamless, free-form speech editing is now feasible. This capability is significant because it bridges the critical gap between understanding and generation.

2.2 Unified Speech Understanding and Generation Models

Recent efforts have aimed to build unified models for speech understanding and generation. KimiAudio (KimiTeam et al., 2025) proposes an audio tokenizer that concatenates the semantic audio token with continuous acoustic vectors from Whisper (Radford et al., 2023a) encoder to enhance perception capability and output a discrete semantic token. DualSpeechLM (Wang et al., 2025c) proposes a dual token modeling paradigm, using a dedicated USToken for input and an acoustic token for output. Other models like SpeechGPT (Zhang et al., 2024), and Moshi (Défossez et al., 2024) have explored different strategies, often relying on large-scale paired data or exhibiting limitations in truly unified representation. Our unified tokenizer offers a more inherent and continuous representation of semantic and acoustic information, which is effective for both generation and understanding tasks. Furthermore, our token-level autoregressive diffusion head for generation is hypothesized to yield higher generation quality compared to a discrete token followed by a sentence-level diffusion module, which has been proved by DitAR (Jia et al., 2025) and VibeVoice (Peng et al., 2025).

2.3 Instruction-Guided Speech Editing

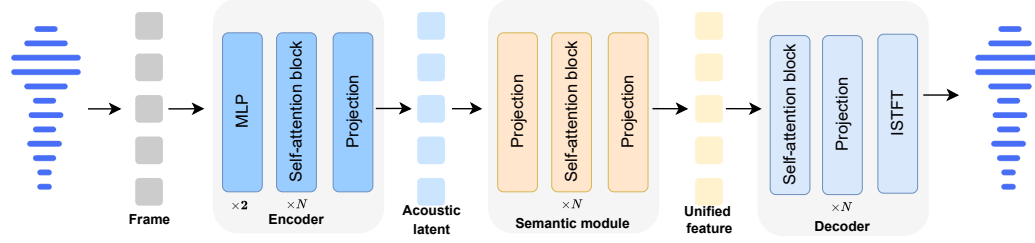
The field of speech editing has seen growth, particularly with instruction-guided approaches. VoiceBox (Le et al., 2023) introduced a non-autoregressive editing paradigm based on flow matching. However, its reliance on alignment models like MFA to specify the editing region adds operational overhead in practical scenarios. InstructSpeech (Huang et al., 2024) represents a significant advancement, employing triplet data construction, multitask learning, and multistep reasoning to enable instruction-based editing. However, when free-form instructions are given, a timestamp alignment mechanism is still required to locate the specified region. Other models, like VoiceCraft (Peng et al., 2024) and EdiTTS (Tae et al., 2021), often have limitations in truly "free-form" capabilities, either requiring explicit region masking or being restricted to specific types of edits. Furthermore, paralinguistic tasks, including emotion and accent conversion, require that a speech LLM possesses strong comprehension abilities. Our framework directly addresses this by enabling comprehensive, unconstrained editing based solely on natural language instructions.

3 Model Architecture

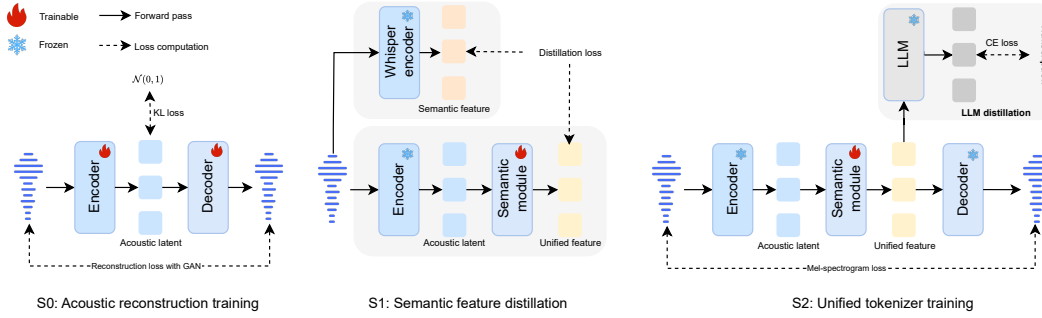
3.1 Unified Continuous Tokenizer

Our unified streaming tokenizer is the cornerstone of Ming-UniAudio, designed to resolve the representation inconsistency between understanding and generation by simultaneously extracting semantic and acoustic features in a streamable manner.

3.1.1 Design Principles and Rationale



(a) The architecture of MingTok-Audio.



(b) Three training stages.

Figure 2 The overall framework of MingTok-Audio

Our model design is guided by three core principles that aim to create a unified representation for both understanding and generation tasks.

- Continuous Representations** A principal challenge in developing a unified model for both understanding and generation tasks lies in the divergent nature of their preferred input representations. Understanding tasks demonstrably benefit from continuous features that better capture nuanced semantic information. Conversely, state-of-the-art speech generation models typically rely on discrete tokens, which, when combined with frameworks like flow matching and vocoders, offer an effective modeling approach. To construct a truly unified architecture, a single and coherent representation is imperative. Discrete tokens are suboptimal for comprehension tasks due to issues such as semantic fragmentation. Furthermore, recent work such as DitAR (Jia et al., 2025) has demonstrated that continuous latent representations of VAE can outperform discrete tokens in generative quality. Therefore, we employ a VAE-based tokenizer that generates a continuous and unified representation for all downstream tasks.
- Joint Modeling of Low- and High-Dimensional Representations** This unified representation (Z_{uni}) presents a core dimensionality challenge. On the one hand, comprehension tasks require high-dimensional, semantically rich inputs for the LLM. On the other hand, generative

frameworks such as flow matching often face scalability challenges with high-dimensional data, making low-dimensional latents (e.g., 32 or 64 dimensions) a more tractable choice for modeling. To bridge this dimensionality gap, our tokenizer is designed to explicitly link the low- and high-dimensional spaces. This is achieved through a semantic module that maps the compact latent variable Z_{latent} , to its semantically richer counterpart Z_{uni} , which is then established as input for the LLM. This architecture advantageously enables all tasks to operate from a rich, high-dimensional space while harnessing the efficiency of a compact latent for generation.

- **Joint Optimization of Semantic Alignment and Acoustic Reconstruction** Our unified representation is optimized with a joint objective that simultaneously targets semantic alignment and acoustic reconstruction. (1) **Semantic Alignment with a pre-trained LLM.** To enrich Z_{uni} with semantics, we use a frozen LLM as a guide. The tokenizer is trained by backpropagating gradients from a discriminative task through the LLM, which forces Z_{uni} to align with the LLM’s semantic space. (2) **Acoustic Reconstruction.** For generation tasks, it is crucial that Z_{uni} retains sufficient low-level acoustic details. We achieve this using Z_{uni} as the input to a reconstruction decoder, tasked with speech reconstruction. This objective of reconstruction forces Z_{uni} to encode fine-grained acoustic details for accurate signal reconstruction. By jointly optimizing for these two objectives, Z_{uni} becomes a single representation encoding both rich semantics for comprehension and fine-grained acoustics for generation.

3.1.2 Tokenizer Architecture

Our tokenizer, detailed in Figure 2a, is a fully transformer-based architecture designed for high efficiency. It is entirely convolution-free and consists of three core modules: an encoder, a semantic module, and a decoder.

- **Encoder** The encoder processes the raw audio input and encodes it in a latent space, following a strategy similar to the TS3-Codec (Wu et al., 2025b). We reshape the raw waveform into a 2D tensor, and then each frame vector is projected into the model’s hidden dimension (d_{model}). Subsequently, we employ a unidirectional transformer to capture contextual information. And its final hidden state is projected to a $2 \times d_{\text{latent}}$ vector to obtain VAE’s latent Gaussian distribution.
- **Semantic module** To obtain a unified representation for downstream understanding and generation training, we introduce a semantic module built upon the pre-trained Whisper large-v3 (Radford et al., 2023b) encoder. We adapt this encoder by removing its convolution layers, enabling it to directly process low-dimensional acoustic latents Z_{latent} from our VAE to high-dimensional unified features Z_{uni} .
- **Decoder** The decoder reconstructs the waveform from Z_{uni} in a two-stage process. First, a unidirectional transformer maps Z_{uni} to an intermediate spectral representation. A subsequent synthesis head, inspired by Vocos (Siuzdak, 2023), then predicts the full complex spectrogram (magnitude and phase) for the final synthesis via an Inverse Short-Time Fourier Transform (iSTFT).

3.2 Unified Speech Language Model

As illustrated in Figure 3, the core of our unified speech language model is a decoder-only LLM backbone. This architecture is designed to process a combined sequence of tokens, seamlessly

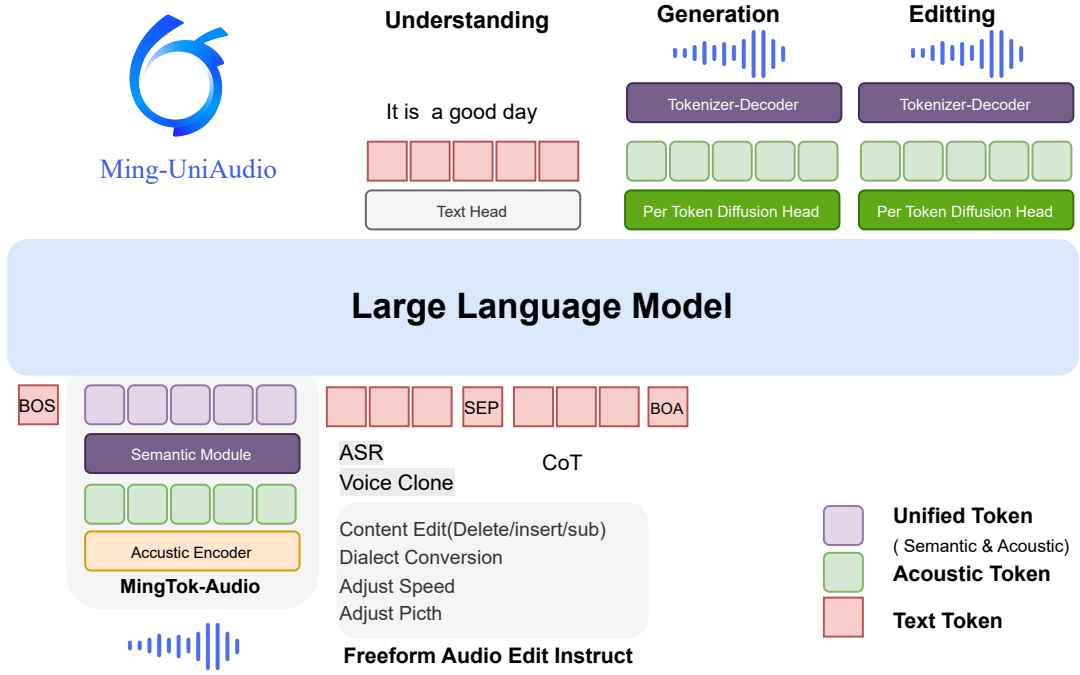


Figure 3 Model Archieture of Ming-UniAudio

integrating text tokens with the continuous unified speech tokens Z_{uni} produced by MingTok-Audio. The model’s versatility is enabled by a multi-head design, where different tasks are handled by specialized output modules. This unified framework allows a single model to pivot between comprehension, synthesis, and manipulation, conditioned on the specific input format and instructional prompts.

- **Understanding tasks:** The LLM’s final hidden states are projected by a text head to auto-regressively generate the target text sequence.
- **Generative tasks:** The hidden states are fed into a per-token diffusion head to synthesize the audio.
- **Editing tasks:** Leveraging this entire architecture in a "understand-then-synthesize" paradigm, the model first processes the source audio and a textual instruction to generate an intermediate representation (e.g., Chain-of-Thought), and then the per-token diffusion head synthesizes the final edited audio.

4 Unified Tokenizer: Methodology and Training

To effectively obtain a unified representation for both speech understanding and generation, we design a three-stage training method for the proposed architecture.

4.1 Three-Stage Training Paradigm

4.1.1 Acoustic reconstruction training

In the first stage, we train an acoustic tokenizer, consisting of the encoder and the decoder, to learn a high-quality representation of the audio waveform. This process is optimized through a hybrid VAE-GAN objective, following the X-codec framework (Ye et al., 2024). As shown in Figure 2b (S0), the overall training objective is composed of two main loss functions, one for the discriminators(D) and one for the generator(G). The discriminator loss, \mathcal{L}_D , aims to distinguish real audio from reconstructed audio over all subdiscriminators. The generator loss, \mathcal{L}_G , is a composite objective designed to ensure both the accuracy of the reconstruction and the naturalness of perception. As shown in Equation 1,

$$\mathcal{L}_G = \lambda_{\text{rec}}\mathcal{L}_{\text{rec}} + \lambda_{\text{adv}}\mathcal{L}_{\text{adv}} + \lambda_{\text{fm}}\mathcal{L}_{\text{fm}} + \lambda_{\text{kl}}\mathcal{L}_{\text{KL}} \quad (1)$$

where the components are: (1) a multi-scale mel-spectrogram reconstruction loss (\mathcal{L}_{rec}) to ensure perceptual audio quality; (2) an adversarial loss (\mathcal{L}_{adv}) to enhance audio naturalness by deceiving the discriminators; (3) a feature matching loss (\mathcal{L}_{fm}) on the discriminator features to stabilize GAN training; and (4) a KL-divergence loss (\mathcal{L}_{KL}) to regularize the VAE’s latent space.

4.1.2 Semantic feature distillation

We initialize the semantic module with the weights of a pre-trained Whisper large-v3 encoder, with the help of its strong semantic priors. To adapt this module from its original mel spectrogram input to our model’s acoustic latent input, we employ semantic distillation, where only the semantic module is trained, as shown in Figure 2b (S1). As defined in Equation 2, Z_{semantic} is the output of the original frozen Whisper encoder.

$$\mathcal{L}_{\text{distill}} = \text{MSE}(Z_{\text{uni}}, Z_{\text{semantic}}) \quad (2)$$

4.1.3 Unified tokenizer training with LLM

Following the methodology outlined in Section 3.1.1, we perform a joint training phase for semantic alignment and speech reconstruction. During this stage, we exclusively update the parameters of the semantic module, forcing Z_{uni} to simultaneously capture both rich semantic content and detailed acoustic features. Unlike the acoustic reconstruction training stage, the training for this task is guided only by the mel-spectrogram reconstruction loss, as we found that including GAN losses at this stage negatively impacts semantic learning.

$$\mathcal{L}_{\text{align}} = - \sum_{t=1}^T \log P(y_t | Z_{\text{uni}}, y_{<t}) \quad (3)$$

$$\mathcal{L} = \lambda_{\text{align}}\mathcal{L}_{\text{align}} + \lambda_{\text{rec}}\mathcal{L}_{\text{rec}} \quad (4)$$

4.2 Experimental Setup

4.2.1 Data & Evaluation Metrics

Our model is trained on a vast and diverse corpus of approximately 390,000 hours of speech data(16kHz), with a balanced 1:1 ratio of Mandarin Chinese and English. For evaluation, we report

results on the public Seed-TTS-Eval (Anastassiou et al., 2024a)¹ benchmark. To comprehensively evaluate the performance of our proposed unified tokenizer, we employ several widely used objective metrics. (1) Short-Time Objective Intelligibility (STOI); (2) Perceptual Evaluation of Speech Quality (PESQ); (3) Speaker Similarity (SPK SIM).

4.2.2 Training configurations

Our unified tokenizer processes 16 kHz audio by segmenting it into non-overlapping frames of 320 samples, resulting in a 50 Hz frame rate with sliding window attention (window size=32) in all layers. Our model has a total of 1.35B parameters. We train our tokenizer following the three-stage training paradigm proposed in Section 4.1. The specific configurations for each stage are detailed in Table 1.

Training stage	Learning rate	Training steps	Trainable modules	Objectives
Acoustic tokenizer training	1e-4	200k	Encoder+ Decoder	$\mathcal{L}_G = 15\mathcal{L}_{\text{rec}} + \mathcal{L}_{\text{adv}} + \mathcal{L}_{\text{feat}} + 1e^{-4}\mathcal{L}_{\text{KL}}$
Semantic feature distillation	1e-4	200k	Semantic module	$\mathcal{L} = \mathcal{L}_{\text{distill}}$
Unified tokenizer training	1e-4	200k	Semantic module	$\mathcal{L} = 2\mathcal{L}_{\text{align}} + \mathcal{L}_{\text{rec}}$

Table 1 Training Configurations for Unified Continuous Speech Tokenizer

4.3 Evaluation

4.3.1 Speech Reconstruction Performance

The evaluation is performed according to the methods described in Section ?? . As shown in Table 2, our tokenizer demonstrates substantially superior performance in all metrics evaluated under the same conditions. This result strongly indicates that, under the continuous VAE modeling paradigm, the acoustic information of the raw speech is preserved with high quality.

System	FrameRate	SEED-ZH			SEED-EN		
		PESQ↑	SIM↑	STOI↑	PESQ↑	SIM↑	STOI↑
MingTok-Audio(ours)	50	4.21	0.96	0.98	4.04	0.96	0.98
MiMo-Audio-Tokenizer Xiaomi (2025)	25	2.71	0.89	0.93	2.43	0.85	0.92
GLM4-Voice-Tokenizer Zeng et al. (2024)	12.5	1.06	0.33	0.61	1.05	0.12	0.60
Baichuan-Audio-Tokenizer Li et al. (2025b)	12.5	1.84	0.78	0.86	1.62	0.69	0.85
XY-Tokenizer Gong et al. (2025)	12.5	2.27	0.77	0.90	2.14	0.82	0.90
Mimi Défossez et al. (2024)	12.5	2.05	0.73	0.89	2.01	0.77	0.89
XCodec2.0 Ye et al. (2025)	50	2.19	0.80	0.92	2.37	0.82	0.93
BigCodec Xin et al. (2024)	80	2.26	0.81	0.92	2.22	0.80	0.91

Table 2 Comparison of reconstruction performance across different acoustic tokenizers.

4.3.2 Downstream TTS Performance

To validate the capabilities of our unified tokenizer for generation, we evaluated its performance on downstream TTS tasks. Z_{uni} serves as the input to the LLM and a per-token flow matching head is employed for generative modeling. The results are presented in Table 3. Our continuous feature-based TTS, built upon the unified tokenizer, significantly outperforms our previous discrete-token model, Ming-lite-omni, despite using the same training data and model scale. This result highlights the superiority of the unified representation for generative tasks.

¹<https://github.com/BytedanceSpeech/seed-tts-eval>

System	Seed-zh WER(%)	Seed-zh SIM	Seed-en WER(%)	Seed-en SIM
Seed-TTS Anastassiou et al. (2024b)	1.12	0.80	2.25	0.76
Ming-Omni-Lite Inclusion et al. (2025)	1.69	0.68	4.31	0.51
MingTok-Audio-TTS	1.04	0.75	1.54	0.68

Table 3 Performance of MingTok-Audio on the downstream TTS task.

5 Pre-training the Unified Speech Language Model

5.1 Methodological Insights for Unified Pretraining

The primary objective of the pretraining stage is to enable the Speech LLM to achieve state-of-the-art performance on both understanding and generation tasks. This is of significant importance for downstream applications, such as audio editing and contextual understanding. However, unified training of understanding and generation tasks presents inconsistencies in terms of iteration steps, convergence speed, and hyperparameters. To address these training inconsistencies, we distill the following methodological insights that proved crucial for pre-training:

- **Stability of Representation:** The speech tokenizer MingTok-Audio, when independently validated on downstream understanding and generation tasks, can achieve strong performance. This indicates that the unified representation of MingTok-Audio, denoted as Z_{uni} , is inherently rich in both semantic and acoustic information. However, there are disparities between the two tasks in terms of data volume, training steps, and learning rates. A stable representation is fundamental for both tasks. However, unfreezing all parameters (i.e. full fine-tuning) can easily lead to feature drift, resulting in an imbalanced performance between understanding and generation. Consequently, freezing the tokenizer and selecting a parameter-free token compression module, especially during the initial training phase, is crucial for maintaining the stability of the tokenizer’s semantic and acoustic representations.
- **Closed-loop Flow of Representation:** Semantic and acoustic features must be able to flow in a closed loop throughout the training process. Otherwise, representation skew may occur, biasing the model’s performance towards a specific task. It is crucial that in modules such as the tokenizer’s semantic module, adapters of LLM, token compressor, and per-token flow matching head, both semantic and acoustic information can be freely transmitted. This prevents the representation from wavering between understanding and generation objectives at any stage, a phenomenon we term "*Representation Confusion*".
- **Joint Training:** Tasks with different convergence steps, volumes of training data, and levels of difficulty must be properly scheduled. Performance in understanding tasks is typically positively correlated with the number of tokens consumed. In contrast, the performance of speech generation, using an autoregressive model with a per-token diffusion head, is generally associated with the number of iteration steps. Therefore, to efficiently utilize computational resources and enable both understanding and generation tasks to achieve optimal performance simultaneously, a specific strategy should be adopted.

5.2 Implementation Details

The overall architecture employs a 16.8B-parameter Mixture-of-Experts (MoE) large language model (2.8B active) for autoregressive generation, as illustrated in Figure 3.

Audio Token Compression is one of the most influential strategies. After the audio tokenizer generates high-dimensional features from the input audio, there are multiple approaches to downsample the feature sequence to the desired input frame rate of the LLM. In addition to the temporal pooling method that operates on adjacent tokens shown Equation 5, an alternative approach (cross-attention compressor) involves employing a transformer module to aggregate information from the chunk into the [CLS] token.

$$Z'_{\text{uni}}[i] = \text{Pooling}(Z_{\text{uni}}[pi : (p+1)i]) \quad \text{for } i = 0, \dots, \left\lfloor \frac{l_{\text{uni}}}{p} \right\rfloor - 1 \quad (5)$$

where l_{uni} is the length of Z_{uni} . To investigate the influence of the two methods, we conducted a study whose results are shown in Table 4. Clearly, the pooling strategy achieves significantly better results. This suggests that the downsampling process itself does not require a highly complex mapping. Still, an efficient and accurate transmission of the original features is required to maximize the information available to downstream modules.

Configuration	Und WER(%) ↓							Gen WER(%) ↓ SIM↑		
	aishell1	aishell2-ios	Fleurs-zh	LS-clean	LS-other	Voxpopuli-en	AVG	Seed-zh	Seed-en	AVG
Baseline (pooling)	3.23	3.62	5.53	2.26	6.02	10.41	5.18	8.07 0.61	22.07 0.39	15.07 0.50
Baseline (cross-attention)	5.69	7.05	6.95	3.64	10.06	13.97	7.89	8.88 0.48	21.89 0.26	15.39 0.37

Table 4 Performance comparison of the downsampling strategies. Both experiments are performed on Qwen-0.5B.

Semantic Module Freezing During the early stages of pre-training, the output feature distribution of the semantic module may undergo significant changes during training of understanding and generation tasks, leading to unstable convergence or slower convergence rates. A comparative experiment on this phenomenon is presented in Table 5 and Figure 5a. As can be observed, when the semantic module is not frozen, the performance of both the understanding and the generation tasks deteriorates significantly, and its convergence speed is slower. This indicates the presence of a clear representation inconsistency between understanding and generation tasks.

Diffusion Head Initialization To accelerate the convergence of the unified speech language model, we aim to verify whether initializing the diffusion head parameters with those already trained on generation tasks can lead to a better result. Thus, we trained a Qwen-0.5B based model in a single-task manner with the same training setup and loaded its weights before the large-scale training started. We evaluated the performance of this strategy on Qwen-0.5B, and the results are presented in Table 5 and Figure 5b. With almost no degradation in the performance of the understanding task, the performance of the generation task is significantly improved. In addition, the baseline configuration with diffusion head initialization achieves a convergence speed approximately 2.0 times that of the ablation experiments.

Stopping Criterion For Generation with Continuous Token Unlike the discrete tokenizer, which benefits from a special <EOS> token, our model requires an additional stop detector. We append a linear layer to the LLM that performs binary classification at each frame. To avoid a strong dependence on tail annotation, we propose a weakly supervised training strategy. (1) The last frame of each utterance is labeled as the positive sample(stop); (2) Then the previous three frames(300ms) of the last frame were ignored to minimize the impact of VAD errors; (3) Among the remaining frames, one frame with the highest stop score was selected as the negative sample. This method

Configuration	Und WER(%) ↓							Gen WER(%) ↓ SIM↑		
	aishell1	aishell2-ios	Fleurs-zh	LS-clean	LS-other	Voxpopuli-en	AVG	Seed-zh	Seed-en	AVG
Baseline	2.29	3.32	4.26	2.28	6.04	7.91	4.35	4.62 0.58	8.43 0.39	6.53 0.49
+ Task dist. = 1 : 3	2.38	3.33	4.39	2.33	5.90	8.29	4.44	3.18 0.60	5.54 0.42	4.36 0.51
+ Task dist. = 1 : 4	2.47	3.43	4.35	2.40	6.13	8.13	4.49	3.20 0.60	5.75 0.44	4.48 0.52
– Semantic module freezing	4.02	4.54	7.21	2.81	7.81	14.78	6.86	8.11 0.60	22.49 0.39	15.30 0.50
– Diffusion head init	2.36	3.33	4.22	2.27	5.92	7.92	4.34	10.02 0.51	12.64 0.32	11.33 0.42
Baseline 420k steps	1.62	3.08	4.33	1.76	4.91	8.46	4.03	2.27 0.63	6.59 0.44	4.43 0.54
+ Annealing	1.47	2.82	4.06	1.59	4.39	8.37	3.78	1.97 0.64	6.05 0.46	4.01 0.55

Table 5 Performance comparison of several training strategies.

keeps a balance of positive to negative samples and mines the hardest negative samples online. The stop head is trained with a cross-entropy loss scaled by a factor of 0.01.

5.3 Data Curation and Processing

The performance of our model relies on a large-scale, diverse training dataset. We compiled our data from two primary sources: publicly available audio datasets and an in-house collection comprising web-crawled recordings and synthetically generated audio.

To ensure data quality and relevance, we implemented a multi-stage preprocessing pipeline. First, a rigorous cleaning process is applied to all data, particularly to the web-crawled audio which exhibits significant quality variance. Second, recognizing that different tasks such as understanding and generation have distinct requirements, we perform task-specific filtering. This tailored approach allows us to create high-quality, annotated data subsets optimized for a wide range of speech-related tasks, forming a solid foundation for training our unified model.

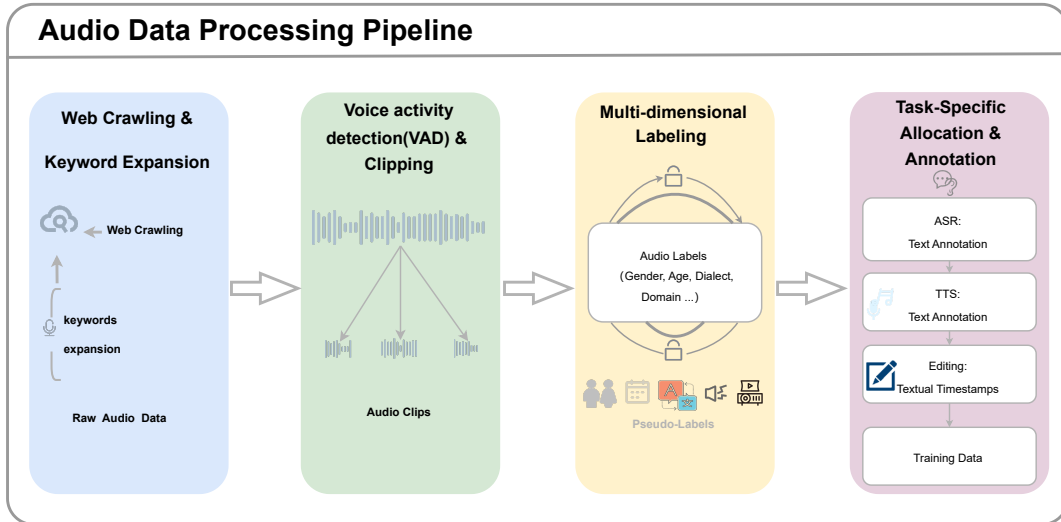


Figure 4 Overview of Audio Data Processing Pipeline.

5.4 Training

Large-scale training stage This stage aims to provide the LLM with enough large-scale data to establish its fundamental alignment capability. During this phase, the model was trained for 200,000

steps, with a 1:3 training step ratio between understanding and generation tasks. Throughout the entire training process, the parameters of the semantic module within the audio tokenizer were kept frozen.

Annealing stage The purpose of this stage is to perform annealing using higher-quality data and a smaller learning rate, thereby stabilizing the model parameters while further improving the overall performance. All other training configurations remain the same as in the previous stage.

Full fine-tuning stage This stage continues training with the unfrozen semantic module parameters, building on the previous stage. At the same time, the proportion of generation task training is moderately increased, with the aim of further improving the performance of the generation task while minimally affecting the performance of the understanding task.

Hyper-parameter	Pre-training		
	Large-scale training	Annealing	Full fine-tuning
LR (Semantic Module)	frozen	frozen	1e-5
LR (Others)	1e-4	1e-5	1e-5
LR scheduler	constant	constant	constant
batch size (Und)	5500 tokens	5500 tokens	5500 tokens
batch size (Gen)	2000 tokens	2000 tokens	2000 tokens
step ratio (Und:Gen)	1:3	1:3	1:6
warmup steps	3000	0	0
AdamW eps	1e-5	1e-5	1e-8
Training data duration(h) (Und:Gen)	400k:800k	370k:370k	370k:370k

Table 6 Training configuration across different stages. LR stands for learning rate. Und stands for understanding. Gen stands for generation.

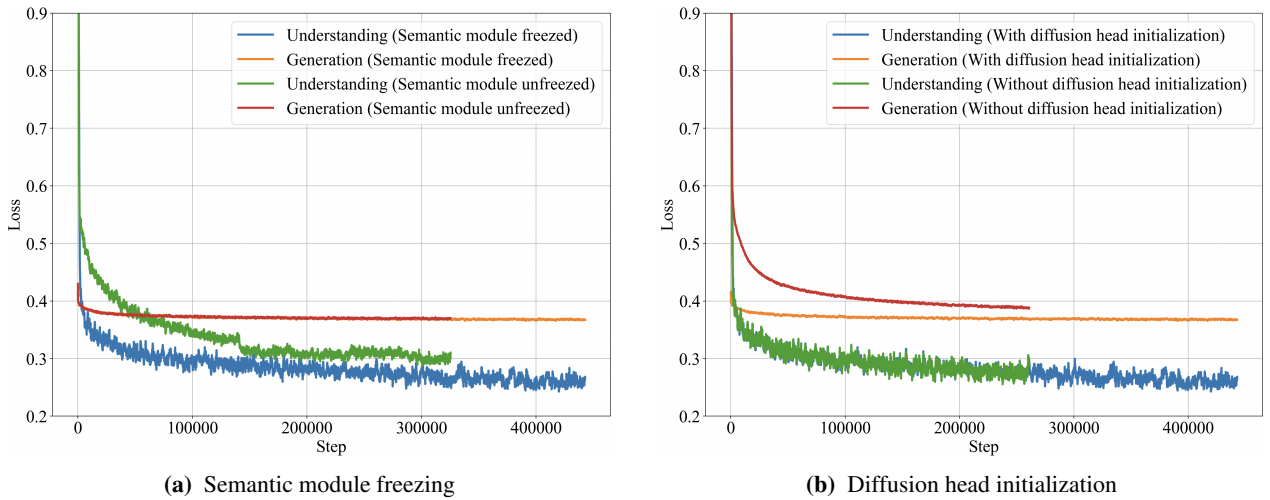


Figure 5 The loss curve of the ablation study for semantic module freezing and diffusion head initialization.

6 Instruction-based Free-Form Speech Editing

6.1 Unified Paradigm for Instruction-Based Editing

Speech editing is a task that places high demands on both understanding and generation capabilities simultaneously. Leveraging the strong foundational capabilities of the Ming-UniAudio model in

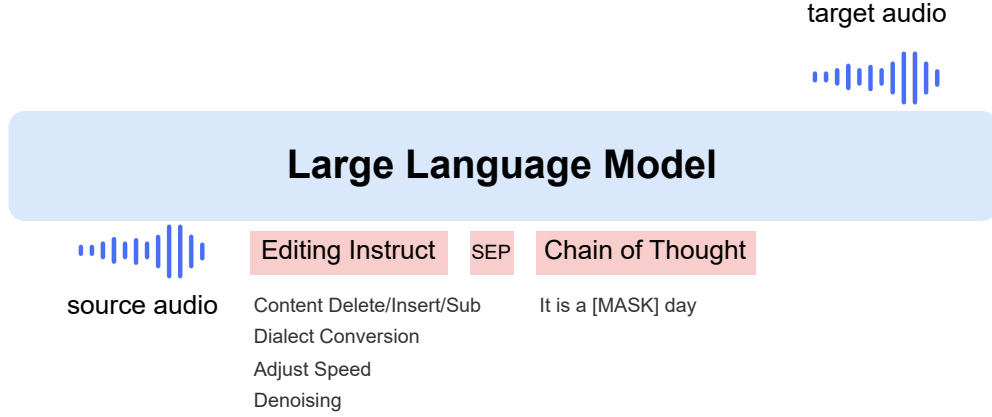


Figure 6 Comparison of Ming-UniAudio with Open-Source Speech LLMs across Understanding, Generation, and Editing Tasks.

both understanding and generation, we explore the training paradigms, data construction methods, and evaluation metrics for free-form instruction-based speech editing. The core challenge in unifying speech understanding and generation stems from a fundamental inconsistency in representation. Understanding tasks thrive on continuous, semantically rich features, while state-of-the-art generation models often rely on discrete tokens. Although effective for synthesis, these discrete tokens sacrifice fine-grained acoustic information, which in turn degrades performance on understanding tasks. This forces a fragmented approach: using continuous tokens for understanding and discrete ones for generation. The result is two disparate tokenization schemes that fundamentally prevent the development of a truly unified, high-quality representation.

Building upon a pre-trained, continuous and unified tokenizer MingTok-Audio, as well as a pre-trained Speech LLM Ming-UniAudio that unifies both understanding and generation tasks, our approach enables high-quality speech understanding and speech generation using a single, unified representation. This architecture perfectly aligns with the "understand-then-synthesize" paradigm required for speech editing tasks as shown in Figure 6. Ultimately, our model supports a variety of editing tasks. The corresponding input and output formats for each task are detailed in Table 7. To the best of our knowledge, this is the first speech editing model capable of following human instructions without requiring any additional operations such as timestamp alignment.

Type	Task	Input	Output
Semantic	Deletion	SourceSpeech, delete the word 'hello' in...	CoT _{text} , TargetSpeech
	Insertion	SourceSpeech, insert the word 'hello' in...	CoT _{text} , TargetSpeech
	Substitution	SourceSpeech, substitute the word 'hello' with 'world'	CoT _{text} , TargetSpeech
Acoustic	Denoise	SourceSpeech, denoise the audio	TargetSpeech
	Speed Alteration	SourceSpeech, adjust the speed to 1.5	TargetSpeech
	Pitch Alteration	SourceSpeech, shift the pitch by 3 steps	TargetSpeech
	Volume Alteration	SourceSpeech, adjust the volume to 1.5	TargetSpeech
	Dialect Conversion	SourceSpeech, change the accent of the speech to Chengdu	TargetSpeech

Table 7 A summary of various speech editing tasks and their task formulation.

We designed the training scheme for free-form instruction-based editing based on *following principles*:

- **Global vs. Local:** Semantic and acoustic editing tasks exhibit a fundamental local versus global distinction. Semantic editing is typically local: it modifies content within a specific region while requiring the surrounding audio (content, timbre, prosody) to remain unchanged. The edited segment must also maintain acoustic consistency with its context. In contrast, acoustic editing (e.g., accent conversion, denoising) is often global, altering acoustic features across the entire utterance while preserving the original text. This distinction requires different modeling approaches.
- **Locate then Modify:** Given their local nature, semantic editing tasks require a two-stage process: first locating the target segment and then performing the modification, which we formulate as a Chain of Thought for Semantic Tasks.
- **Joint Training of Complementary Tasks:** Many training tasks can be viewed as complementary pairs, such as denoising versus adding background music, and text addition versus deletion. Consequently, multitask joint training is expected to enhance overall model performance by leveraging these complementary relationships.

Based on these principles, we propose a unified generative model that seamlessly integrates semantic understanding and acoustic synthesis. To address the "Global vs. Local" distinction, our model operates on the unified representation (Z_{uni}) for content manipulation and uses a per token diffusion head for high-quality generation, accommodating both local semantic edits and global acoustic changes. For the "Locate then Modify" principle in semantic tasks, we formulate the process as an instruction-guided sequence-to-sequence transformation: the model first autoregressively generates a target semantic sequence, effectively performing a "chain-of-thought" reasoning to determine the edited content and its location.

Acoustic Tasks We have designed a unified paradigm for a wide array of acoustic editing tasks. These include paralinguistic modifications like emotion and dialect conversion, physical attribute adjustments such as speed, pitch, and volume, and other tasks like denoising and adding background sound. This framework takes an input audio and an instruction to produce an edited audio output directly. Crucially, it avoids generating any textual or other semantic outputs, which allows it to accommodate diverse types of output audio flexibly. This paradigm demonstrates powerful robustness and performs exceptionally well across various content-preserving editing tasks, where the underlying textual content remains unchanged.

Semantic Tasks For semantic editing tasks, we adopt an instruction-following format allowing us to effectively leverage the pre-trained model’s ability to comprehend and execute instructions. The data is structured as follows:

$$\text{SourceSpeech}_{z_{\text{uni}}} + \text{Instruction}_{\text{text}} \rightarrow \text{CoT}_{\text{text}} + \text{TargetSpeech}_{z_{\text{latent}}}$$

We introduced several key innovations to achieve free-form instruction following:

- **CoT for Textual Guidance:** We incorporate a chain-of-thought (CoT) (Wei et al., 2023) step where the model first generates the target text of the edited speech. This intermediate textual output significantly improves the pronunciation accuracy and instruction-following capabilities of the final synthesized audio.
- **Explicit Edit Localization:** Inserting a special [MASK] token into the CoT text explicitly demarcates the edit region. This provides the model with precise positional cues, guiding its focus to the intended segment for modification and enhancing its positional awareness.

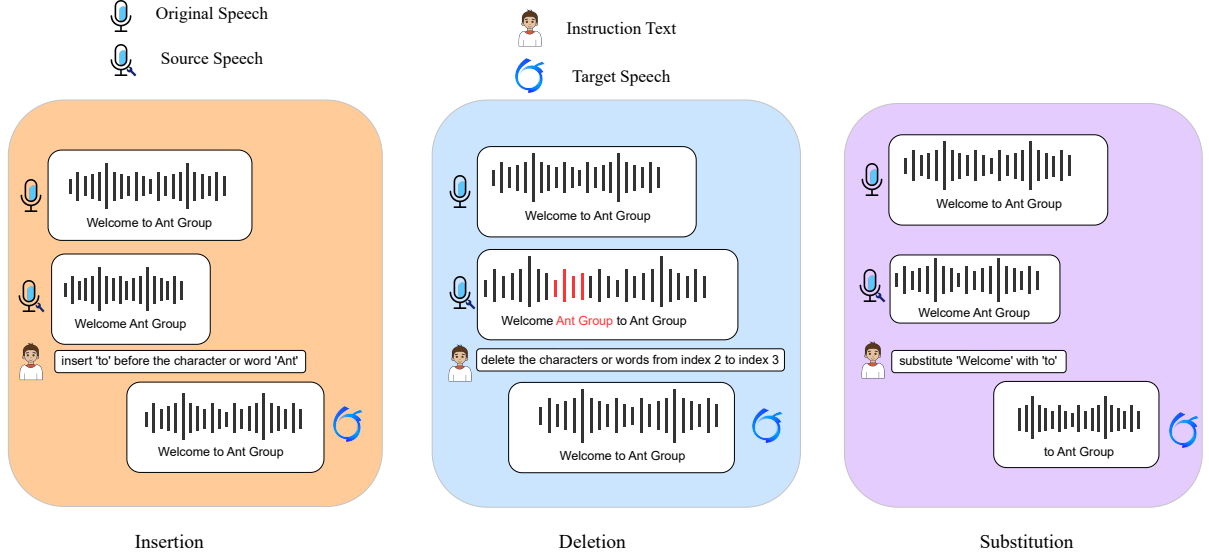


Figure 7 Speech Edit Data Construction Method

- **Weighted Loss for Edited Regions:** To prioritize learning the complex synthesis of new content, a higher loss weight is applied to the edited audio segments. This strategy distinguishes these regions from non-edited ones, where reconstruction can be simplified by copying from the source audio.

6.2 Instruct Tuning Data

We construct speech editing training dataset by the following methods as shown in Figure 7:

Insertion: This task involves inserting content at a specified position, which can be defined by a text index or as a location relative to a specific word (i.e., before or after it). Training pairs are constructed with an audio segment that contains a removed portion as input and the original complete audio as the target.

Deletion: As a dual of insertion, this task aims to remove specified content. We synthesize the input by inserting a random audio artifact into a clean recording. The target is the original, unmodified audio, thus training the model to remove the artifact.

Substitution: This task aims to replace a segment of audio with different content. We construct the input by relocating a segment of the original audio to overwrite a different, non-overlapping segment within the same recording. The target is the original, unmodified audio, training the model to restore the overwritten section.

Denoising: Noisy inputs are generated by augmenting clean audio with noise from the MUSAN (Snyder et al., 2015) dataset. The target is the original, clean audio.

Speed and Pitch Alteration: We processed the audio using open source tools to alter its speed and pitch. The processed audio served as the training target, with the original audio and an instruction as input.

Dialect Conversion: We built a Mandarin-dialect parallel corpus. To enrich speaker diversity, we further apply voice conversion (VC) to generate over 1,000 distinct timbres for the training data.

6.3 Freeform-Audio-Edit Benchmark

We construct Ming-Freeform-Audio-Edit, the first universal free-form speech editing benchmark for semantic and acoustic tasks without timestamp condition, including speech content insertion/deletion/substitution, emotion/accent conversion, speed/pitch/volume alteration, etc.

6.3.1 Semantic Test Sets

Public benchmarks for the semantic speech editing task are scarce, which hinders the direct comparison of different methods. In addition, existing evaluation sets are predominantly designed for region-based models. To our knowledge, Ming-Freeform-Audio-Edit is the first benchmark constructed for free-form speech editing models.

Dataset Construction: We select 896 Chinese and 655 English samples from the seed-tts test set. For each audio clip, it is first randomly assigned to one of three tasks: deletion, insertion, or substitution. Next, we obtain its transcription and leverage LLM to generate a natural language instruction for the assigned task and the corresponding edited text. Finally, the edited text generated by the LLM is manually verified to ensure that it aligns with the expected outcome of the given instruction.

Dataset statistics: The instructions for deletion, insertion, and substitution tasks can be broadly categorized into two types: *index-based*, which specifies an operation on content from positions i to j , and *content-based*, which targets specific characters or words for editing.

In our initial version, the editing instructions are written in English for both Chinese and English audio, and their phrasing was relatively limited in variety (see Appendix C for examples of Ming-Freeform-Audio-Edit). We refer to this as the *basic* version; the dataset statistics for this *basic* version are shown in Table 8.

Instruction Type	Zh			En		
	deletion	insertion	substitution	deletion	insertion	substitution
Index-based	92	65	29	47	79	29
Content-based	78	105	130	133	81	150
Total	170	170	159	180	160	179

Table 8 Dataset statistics for *basic* semantic test sets of Ming-Freeform-Audio-Edit.

To better align the editing instructions with the real user expressions, we construct a second version of those test sets, referred to as the *full* version. In addition to increasing the number of test examples per task, we deliberately emphasize the naturalness and diversity of the instructions when generating them with the LLM. Furthermore, our preliminary experiments revealed that the three tasks vary in difficulty, with substitution proving to be the most challenging. Consequently, we increase the proportion of substitution tasks in our test set to ensure a more rigorous evaluation. Detailed statistics of the *full* version dataset are provided in Table 9.

Instruction Type	Zh			En		
	deletion	insertion	substitution	deletion	insertion	substitution
Index-based	186	180	36	138	100	67
Content-based	95	110	289	62	99	189
Total	281	290	325	200	199	256

Table 9 Dataset statistics for *full* semantic test sets of Ming-Freeform-Audio-Edit.

6.3.2 Acoustic Test Sets

Dataset Construction: The construction procedure for the acoustic test sets is similar to that of the semantic test sets: the audio are sourced from the seed-tts test set, and a LLM generates task-specific editing instructions. Unlike the semantic test sets, no text labels are required, eliminating the manual verification step.

Dataset statistics: Per-task test sample counts for the acoustic test sets in Ming-Freeform-Audio-Edit are presented in Table 10.

Task Type	Zh	En
Emotion conversion	84	72
Speed alteration	50	50
Pitch alteration	50	50
Volume alteration	50	50
Dialect conversion	250	–

Table 10 Dataset statistics for acoustic test sets of Ming-Freeform-Audio-Edit.

6.3.3 Evaluation Metrics

For semantic editing task, we report the WER and SIM to respectively assess the intelligibility of speech and speaker similarity following seed-tts (Anastassiou et al., 2024b). In addition, we define ACC and no-edit WER to measure the audio editing accuracy within the editing area and the audio WER outside the editing area. For acoustic editing tasks, the evaluation metrics vary depending on the specific task. Specifically, for the speech denoising task, we use the DNSMOS (Reddy et al., 2022) to evaluate the quality of the enhanced speech. This score ranges from 0 to 5, where a higher score indicates better audio quality. For the remaining tasks, we primarily employ WER and SIM as the evaluation criteria. We also report the relative duration error (RDE) for speed alteration and the relative amplitude error (RAE) for volume alteration; lower values indicate closer adherence to the target specifications.

7 Results and Analysis

7.1 Understanding

As presented in Table 11, Ming-UniAudio achieves performance comparable to leading open-source models on several public benchmarks. Notably, due to its specialized multi-dialect training, it significantly outperforms existing models on our in-house dialect test set.

Furthermore, the model demonstrates a strong capability in leveraging contextual information, as evidenced by its performance on the ContextASR Bench (Wang et al., 2025a). According to the results in Table 12, Ming-UniAudio achieves SOTA performance on 8 of the 12 subtasks. This suggests a strong potential for robust performance in real-world scenarios such as multi-turn dialogue and hotword enhancement.

7.2 Generation

As shown in Table 13, Ming-UniAudio demonstrates strong overall performance in speech generation. For speech intelligibility, measured by Word Error Rate (WER), it achieves the best result on Chinese among the compared models (0.95) and remains highly competitive on English. While

Datasets	Model	Performance					
		aishell2-ios	LS-clean	Hunan	Guangyue	Chuanyu	Shanghai
Understanding ASR	Kimi-Audio KimiTeam et al. (2025)	2.56	1.28	31.93	41.49	6.69	60.64
	Qwen2.5 Omni Xu et al. (2025a)	2.75	1.80	29.31	10.39	7.61	32.05
	Qwen2 Audio Chu et al. (2023)	2.92	1.60	25.88	7.59	7.77	31.73
	Ming-UniAudio	2.84	1.62	9.80	5.51	5.46	14.65

Table 11 Comparison of ASR performance on various audio benchmark datasets. The best results are in **bold**.

Datasets	Model	Performance			
		Speech-English	Dialogue-English	Speech-Mandarin	Dialogue-Mandarin
		WER NE-WER NE-FNR	WER NE-WER NE-FNR	WER NE-WER NE-FNR	WER NE-WER NE-FNR
Understanding Context ASR Wang et al. (2025b)	Qwen2-Audio Chu et al. (2023)	11.49 27.27 35.08	13.99 33.02 32.92	9.92 24.10 30.02	7.00 22.76 26.17
	Baichuan-Audio Li et al. (2025a)	7.52 5.87 4.55	5.66 10.01 3.64	2.16 6.65 2.35	2.96 11.48 3.94
	Kimi-Audio KimiTeam et al. (2025)	2.90 6.68 8.01	4.67 13.50 11.31	1.95 11.13 15.28	2.90 15.91 16.68
	Baichuan-Omni-1.5 Li et al. (2025c)	8.16 7.69 6.53	9.91 14.40 5.54	2.98 8.39 4.71	5.00 16.83 7.84
	Qwen2.5-Omni-3B Xu et al. (2025a)	3.99 7.80 9.69	4.83 14.36 12.85	2.13 10.55 14.11	3.12 15.07 15.17
	Qwen2.5-Omni-7B Xu et al. (2025a)	3.96 7.38 8.72	5.32 11.83 9.24	1.84 9.80 12.19	2.40 14.06 13.17
	Ming-UniAudio	4.00 3.56 3.69	5.34 8.73 2.53	1.58 5.98 2.40	3.04 9.50 1.48

Table 12 Comparison of Contextual ASR performance on ContextASR Bench ([Wang et al., 2025a](#)). The best results are in **bold**.

there is room for further improvement in timbre similarity (SIM), the model consistently produces highly intelligible speech, which is a primary focus of our work.

Datasets	Model	Performance			
		Seed-zh WER(%)	Seed-zh SIM	Seed-en WER(%)	Seed-en SIM
Generation	Seed-TTS Anastassiou et al. (2024b)	1.12	0.80	2.25	0.76
	FireRedTTS Guo et al. (2024)	1.51	0.65	3.82	0.53
	FireRedTTS-2 Xie et al. (2025)	1.14	0.736	1.95	0.65
	DiTAR Jia et al. (2025)	1.02	0.753	1.69	0.74
	F5-TTS Chen et al. (2024)	1.56	0.74	1.83	0.65
	CosyVoice 2 Du et al. (2024c)	1.45	0.75	2.57	0.65
	CosyVoice 3-1.5B Du et al. (2025)	1.12	0.78	2.21	0.72
	MiMo-Audio Xiaomi (2025)	1.96	-	5.37	-
	Qwen2.5-Omni-7B _{RL} Xu et al. (2025a)	1.42	0.75	2.33	0.64
	Qwen3-Omni-30B-A3B-Instruct Xu et al. (2025b)	1.07	-	1.39	-
	Ming-UniAudio	0.95	0.70	1.85	0.58

Table 13 Performance comparison on speech generation benchmark datasets. The best results are in **bold**.

7.3 Editing

Table 14 summarizes the objective results for our editing tasks. Overall, Ming-UniAudio demonstrates robust and versatile editing capabilities across a wide range of semantic and acoustic manipulations.

Semantic Editing: A key feature of Ming-UniAudio-Edit is its ability to perform free-form semantic editing based on natural language instructions. As most existing open-source models lack this capability, direct comparisons are limited. Our internal analysis, however, reveals several key performance trends:

- **Strong Task Performance:** It achieves high accuracy on core tasks, including 79.31% for insertion (WER=3.89) and 76.62% for substitution (WER=4.56).
- **Robust Generalization:** The model shows robust generalization to varying instruction complexities, evidenced by the consistent performance between the *base* and *full* versions of

Ming-Freeform-Audio-Edit.

- **Language and Task Variation:** Performance on Chinese tasks consistently surpasses that of English, likely due to a larger, higher-quality training set. Among the semantic tasks, insertion yields the lowest WER, benefiting from more coherent training targets.

Acoustic Editing: It excels in voice-conversion tasks, notably achieving high stylistic consistency and semantic stability in dialect conversion, alongside strong results in volume and speed alterations. In contrast, pitch alteration presents a challenge to speaker similarity, likely due to target data quality. On DNS Challenge test set (Reddy et al., 2020), its DNSMOS score (3.26 OVRL) is highly competitive with general-purpose models and specialized approaches, validating our unified approach.

Datasets	Model	Performance			
		WER(%) zh en	ACC zh en	SIM zh en	no-edit WER(%) zh en
Deletion-basic Deletion-full	Ming-UniAudio	11.89 14.85	100 82.22	0.78 0.76	11.49 24.26
		22.92 27.60	82.92 85	0.81 0.74	17.50 35.21
Insertion-basic Insertion-full	Ming-UniAudio	3.42 6.63	80 71.43	0.83 0.79	3.52 17.70
		3.89 7.592	79.31 62.31	0.83 0.79	4.10 18.84
Substitution-basic Substitution-full	Ming-UniAudio	4.52 8.99	78.62 59.78	0.82 0.78	4.63 19.28
		4.56 7.64	76.62 65.62	0.83 0.77	4.75 18.39
Dialect conversion	Ming-UniAudio	WER(%)	ACC	SIM	
		8.93	0.50	0.66	
Speed Alteration	Ming-UniAudio	WER(%) zh en	SIM zh en	RDE(%) zh en	
		5.88 17.53	0.66 0.57	6.36 5.92	
Pitch Alteration	Ming-UniAudio	WER(%) zh en	SIM zh en		
		7.45 13.37	0.36 0.24		
Volume Alteration	Ming-UniAudio	WER(%) zh en	SIM zh en	RAE(%) zh en	
		1.71 1.35	0.86 0.80	14.9 11.7	
Add Sound	GroundTruth Ming-UniAudio	WER(%)	SIM	DNSMOS OVRL	
		3.68 3.59	- 0.78	2.12 2.46	
DNS Challenge	Model Type		DNSMOS OVRL	DNSMOS SIG	DNSMOS BAK
	FullSubNet Hao et al. (2021)		3.26	3.54	4.04
	Inter-Subnet Chen et al. (2023)		3.24	3.54	4.00
	CDiffuSE Lu et al. (2022)		1.31	1.89	1.27
	SGMSE Richter et al. (2023)		3.28	3.59	3.97
	StoRM Lemercier et al. (2023)		3.23	3.56	3.92
	MiMo-Audio Xiaomi (2025)		3.30	3.56	4.10
	Ming-UniAudio		3.26	3.59	3.97

Table 14 Performance comparison on Ming-Freeform-Audio-Edit. The best results are in **bold**.

8 Conclusion

Through a multistage training process on the audio tokenizer encompassing reconstruction, feature distillation, and semantic distillation, we have developed a continuous unified representation for speech understanding and generation. In joint training tasks, our model achieves performance on par with leading open-source models, notably reaching state-of-the-art (SOTA) results in the semantic stability of speech generation.

Building upon this unified representation and pre-trained model, we have explored free-form, instruction-based editing that simultaneously handles both semantic and acoustic tasks, showcasing the significant potential of this paradigm. Furthermore, we are open-sourcing our unified tokenizer, pre-trained model, and a speech editing benchmark, inviting more researchers to join us in exploring this promising direction.

9 Future Work

This report outlines our technical approach and preliminary results. In the following, we summarize several directions that we plan to pursue in the near future.

- **Semantic Distillation:** improve large language model distillation to empower understanding performance.
- **Instruction-following generation:** we consider this capability to be a crucial prerequisite for more advanced general-purpose instruction-based speech editing.
- **More modalities:** integrated with modalities of images and videos to achieve multimodal understanding and generation.

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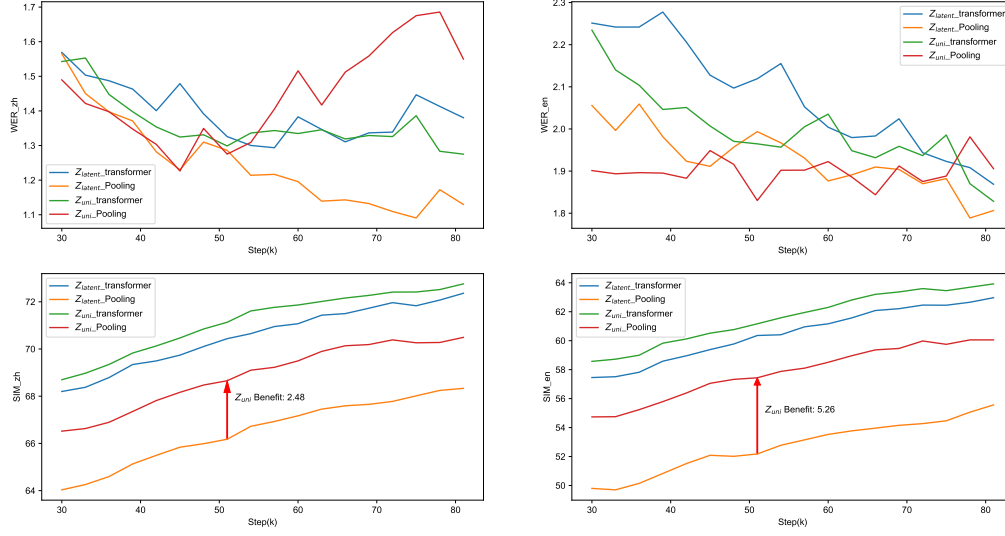


Figure 8 Similarity benefits with Z_{uni} .

Appendix

A Speech Generation

Continuous Speech Tokenization MingTok-Audio originally extracts continuous speech tokens at 50Hz, which proved redundant for speech generation task. We therefore down-sampling the tokens to 10Hz. We experimented with Pooling and transformer architecture. Both Z_{latent} and Z_{uni} experiments have shown that the transformer architecture outperformed. Moreover, the negative effect of pooling on Z_{uni} was substantially smaller than that on Z_{latent} , demonstrating the greater robustness of our unified representation. The pooled Z_{uni} was used for joint training to achieve better understanding performance and faster training speed. As shown in Figure 8(smooth=0.6), the similarity with Z_{uni} is higher than that with Z_{latent} .

Per-Token Generation Head To synthesize high-quality audio, we employ a Flow-Matching objective along the optimal-transport (OT) path. Furthermore, we implement classifier-free guidance (CFG) by randomly dropping the LLM conditioning with probability 0.1 during training. Additionally, as shown in Table 15, MLP with higher computational efficiency is also a good choice.

Size	Step↓	Gen WER(%) ↓ SIM↑			RTF(H20)↓
		Seed-zh	Seed-en	AVG	
DiT(0.1B)	378k	1.040 0.748	1.538 0.682	1.289 0.715	0.61
MLP(1.2B)	174k	1.032 0.733	1.910 0.654	1.471 0.694	0.41

Table 15 Comparison of the flow matching head size.

B Open-source Audio Data

We include the complete list of open source audio data we used during our training in Table 16.

Table 16 The complete list of open-source audio data used during our training.

Dataset	Audio Length (hrs)
WenetSpeech (Zhang et al., 2022)	10518
KeSpeech (Tang et al., 2021)	1428
AliMeeting (Yu et al., 2022)	120
AISHELL-1 (Bu et al., 2017)	155
AISHELL-3 (Shi et al., 2020)	65
AISHELL-4 (Fu et al., 2021)	61
CoVoST (Wang et al., 2020a)	456
CoVoST2 (Wang et al., 2020b)	18
Magicdata (Yang et al., 2022)	747
Gigaspeech (Chen et al., 2021)	10288
Libriheavy (Kang et al., 2024)	51448
LibriSpeech (Zeyer et al., 2021)	960
SlideSpeech (Wang et al., 2024)	473
SPGISpeech (O’Neill et al., 2021)	5000
TED-LIUM (Rousseau et al., 2012)	208
Emilla (He et al., 2024)	90305
Multilingual LibriSpeech (Pratap et al., 2020)	45000
Peoples Speech (Galvez et al., 2021)	30000

C Ming-Freeform-Audio-Edit Examples

C.1 Examples of Basic Semantic Test Sets

C.1.1 Deletion-basic

Instruction: delete ‘The second for’

Original text: The second for no better reason than the first

Edited text: no better reason than the first

Instruction: delete the characters or words from index 6 to index 10

Original text: 火精灵又出现了猴腿帕克挠挠头

Edited text: 火精灵又出克挠挠头

C.1.2 Insertion-basic

Instruction: insert ‘publicly’ after the character or word at index 3

Original text: It does not comment on specific disputes

Edited text: It does not publicly comment on specific disputes

Instruction: insert '的行为很可笑' at the end

Original text: 在他看来像这种用一排大炮来歼灭一只小虫

Edited text: 在他看来像这种用一排大炮来歼灭一只小虫的行为很可笑

C.1.3 Substitution-basic

Instruction: substitute 'a' with 'an outdoor'

Original text: A man wearing a jacket hat and jeans at a market

Edited text: A man wearing a jacket hat and jeans at an outdoor market

Instruction: substitute the characters or words from index 1 to index 2 with '秋天'

Original text: 夏天的酷热过去了冬天的寒冷还早呢

Edited text: 秋天的酷热过去了冬天的寒冷还早呢

C.2 Examples of Full Semantic Test Sets

C.2.1 Deletion

Instruction: Delete the first 4 words.

Original text: Roaming endlessly around the park she wants to go home

Edited text: park she wants to go home

Instruction: 删除“当我们做体验时”

Original text: 当我们做体验时我们到底在做什么

Edited text: 我们到底在做什么

C.2.2 Insertion

Instruction: Start the sentence with 'In practice,'

Original text: To turn this into an algorithm only finitely many frequencies are solved for

Edited text: In practice, to turn this into an algorithm only finitely many frequencies are solved for

Instruction: 在句末添加“大家都很有感动”

Original text: 比如当有人替受伤的小鸟包扎时

Edited text: 比如当有人替受伤的小鸟包扎时大家都很有感动

C.2.3 Substitution

Instruction: Change the last two words to ‘accidentally’

Original text: The boy wanted to believe that his friend had simply become separated from him by accident

Edited text: The boy wanted to believe that his friend had simply become separated from him accidentally

Instruction: 把“不变应万变”换成“静观其变”

Original text: 采取以不变应万变的不卖不赔方法

Edited text: 采取以静观其变的不卖不赔方法

C.3 Instruction Examples of Acoustic Test Sets

Dialect conversion Instructions

- Change the accent of the speech to Chengdu.
- Change the accent of the speech to Dongbei.
- Change the accent of the speech to Guangxi.

Speech changing Instructions

- Adjusts the speed to 0.5
- Adjusts the speed to 1.7
- Adjusts the speed to 1.3

Pitch changing Instructions

- Shifts the pitch by -4 steps
- Shifts the pitch by 6 steps
- Shifts the pitch by -3 steps

Volume changing

- Adjusts the volume to 0.5
- Adjusts the volume to 0.3
- Adjusts the volume to 1.5