StreamFlow: Streaming Audio Generation from Neural Codec Tokens via Streaming Flow Matching

Ha-Yeong Choi[1] **Sang-Hoon Lee**[2,3*]

[1]Gen AI Lab, KT Corp., Seoul, Korea
[2]Department of Software and Computer Engineering, Ajou University, Suwon, Korea
[3]Department of Artificial Intelligence, Ajou University, Suwon, Korea

Abstract

Diffusion models have demonstrated remarkable generative capabilities, and Conditional Flow Matching (CFM) has improved their inference efficiency by following optimal transport paths. However, CFM-based models still require multiple iterative sampling steps, which makes them unsuitable for real-time or streaming generation scenarios. In this paper, we introduce StreamFlow, a novel streaming generative model designed for real-time audio generation from discrete tokens. StreamFlow leverages a causal noising training framework along the time axis and predicts multi-time vector fields at once on each stream, enabling streaming inference with minimal latency. To further improve generalization, we propose Scale-DiT, a Diffusion Transformer architecture that enhances robustness by modeling, normalizing, and scaling feature differences prior to skip connections. This significantly improves the robustness and performance of DiT without increasing the parameter size. We validate the effectiveness of StreamFlow through audio reconstruction tasks using discrete tokens from EnCodec and Mimi, demonstrating both high-fidelity synthesis and streaming capability. Furthermore, we successfully incorporated our model into fully-duplex streaming speech language models of Moshi by replacing the Mimi decoder. Audio samples are available at `https://streamflow25.github.io/demo/`.

1 Introduction

Recently, conditional flow matching (CFM) models [31] have demonstrated powerful generative capabilities across modalities such as text, image, and audio. Initially, CFM was introduced for image-to-image translation and text-to-image generation by conditioning on target labels or text representation such as those from CLIP [42]. Since then, CFM has been extended to a wide range of audio applications, including text-to-speech [24, 10, 4, 8], text-to-audio [41, 26], voice conversion [56, 5, 62], and waveform generation [30, 32, 50]. Additionally, flow matching has been successfully adapted to discrete domains, such as text generation, through discrete flow matching [11]. Most existing CFM approaches focus on parallel generation tasks, such as fixed-size image generation and fixed-length audio generation in a non-autoregressive manner. Although masking and infilling training frameworks with CFM objectives and Transformers [24, 10, 4] can endow the model with in-context learning over long sequences, these models still require numerous sampling steps over a fixed target space, limiting their applicability to real-time streaming generation tasks. To date, streaming

*Corresponding author

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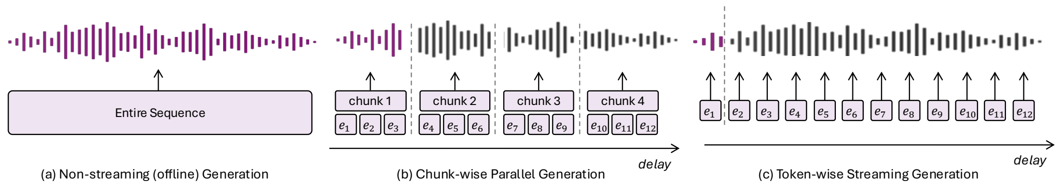


Figure 1: Comparison of generation strategies: (a) Non-Streaming Generation, (b) Chunck-wise Parallel Generation, (c) Token-wise Streaming Generation

generation in diffusion models has largely been explored in video domain. From an engineering perspective, StreamDiffusion [19] introduces the batch denoising method that computes the diffusion process with a batch. Rolling Diffusion [43] introduces a novel DDPM [14] that progressively denoises data over time.

However, to the best of our knowledge, streaming audio generation from discrete tokens has not yet been explored within the frameworks of diffusion or flow matching. While recent parallel generation approaches based on CFM [30] have achieved promising results, they typically operate on a chunk-wise generation, as shown in Figure 1-(b), relying on pre-trained non-autoregressive models. Moreover, generating raw waveform at a high sampling rate (e.g., 24 kHz) introduces additional challenges, as it requires significantly finer resolution compared to lower-resolution acoustic features (e.g., 12.5 and 75 Hz), thus increasing both modeling complexity and computational cost.

Additionally, recent speech language models are getting more attention for end-to-end human-like communication such as GPT-4o [15]. They utilize neural audio codecs with causal layers and GAN-based objective for high-quality waveform generation [7]. However, these models often suffer from perceptual degradation when generating high-resolution waveforms directly from highly compressed, low-bitrate discrete tokens. This is primarily due to the absence of intermediate temporal modeling and progressive refinement, which are essential for maintaining local coherence and preserving fine-grained audio details over time, especially in streaming scenarios where real-time and frame-level consistency are crucial.

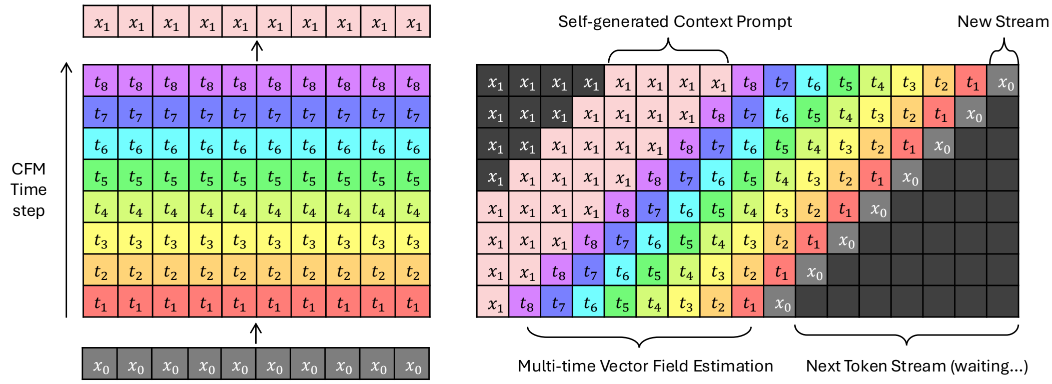
In this paper, we introduce StreamFlow, a novel real-time streaming flow matching model for streaming audio generation. StreamFlow simultaneously estimates multi-time vector fields at each step, thereby offering both streaming generation and refinement capabilities. To facilitate long-range temporal modeling, we adopt diffusion transformers with in-context learning capabilities. In addition, we introduce Scale-DiT, a new diffusion transformer architecture designed to improve feature regularization. Scale-DiT computes the difference between residuals and features, normalizes this difference, and applies a scaling operation before the skip connection. This design improves robustness without increasing model size. We evaluate the effectiveness of StreamFlow on real-time audio reconstruction tasks using discrete tokens from EnCodec [9] and Mimi [7]. Furthermore, we verify that StreamFlow can be seamlessly integrated into existing speech generation pipelines that rely on discrete neural audio codecs. The main contributions of this work are as follows:

- We propose StreamFlow, a novel streaming generative model that leverages self-conditioned context to estimate multi-time vector fields, enabling token-wise streaming generation.
- We introduce a new DiT structure, Scale-DiT that regularizes the feature space by modeling the difference between residual and features, normalizing the difference, and scaling it for elucidating the features.
- We demonstrate the effectiveness of the proposed Streaming Flow Matching framework for streaming audio generation by reconstructing high-quality waveforms in real time from discrete tokens produced by neural audio codecs such as EnCodec and Mimi.

2 Related Work

2.1 Waveform Generation

Conventionally, neural waveform generation tasks have been investigated for text-to-speech systems requiring conversion of acoustic features such as Mel-spectrogram to raw waveform signal, called



(a) CFM

(b) SFM (ours)

Figure 2: Comparison of (a) conditional flow matching (CFM), which performs full-sequence vector field estimation across all timesteps, and (b) streaming flow matching (SFM), our method that leverages self-generated context for multi-time vector field estimation and enables low-latency token-wise streaming.

by *Neural Vocoder*. WaveNet [38] introduced causal dilated convolutional networks to increase the receptive field for high-resolution waveform signal modeling. Due to the slow sampling speed of auto-regressive generation, many works [37, 40, 18] have shifted their focus to parallel waveform generation models for efficient and fast waveform generation. GAN-based parallel models have shown promising parallel generation performance by generating realistic waveform signal. PWG [54] and MelGAN [22] first adopted adversarial training, and HiFi-GAN [20] introduced a novel discriminator, multi-period discriminator (MPD) reflecting implicit periodic features. BigVGAN [25] scaled up the neural vocoder for out-of-distribution robustness by introducing snake activation and an anti-aliasing filter. Then, Vocos [46] boosted the sampling speed by incorporating iSTFT on low-resolution feature space.

2.2 CFM in Waveform Generation

Recently, CFM has been adopted for high-fidelity waveform generation. Although previous diffusion-based models [21, 2] showed slow inference speed and lower performance than GAN-based models, PeriodWave [30], RFWave [32], and FlowDec [50] demonstrated much higher performance on the waveform generation tasks compared to GAN models. Although CFM still requires more sampling steps compared to GAN, they have shown promising results on the waveform generation tasks. Furthermore, PeriodWave-Turbo [28] accelerated CFM-based models by incorporating adversarial feedback, achieving improved performance with smaller sampling steps. However, as shown in Figure 2-(a), streaming generation within the CFM has not been explored.

2.3 Neural Audio Codec

Meanwhile, neural audio codec has garnered more attention than neural vocoder in that it facilitates various practical applications combined with large language models. SoundStream [59] and EnCodec [9] introduced a practical neural audio codec by incorporating residual vector quantization (RVQ) [12, 49] and adversarial training. DAC [23] improved RVQ with carefully designed bottleneck and various losses. HiFi-Codec [55] proposed group-residual vector quantization to increase the capacity of RVQ. SpeechTokenizer [61] and X-Codec [57] distilled the self-supervised speech representation on the quantized representation to increase semantic information without any labeled data. Mimi [7] also introduced a high-compressed low-bitrate audio codec with SSL distillation for an efficient speech language model. Furthermore, single VQ models including WavTokenizer [16], BigCodec [53], and TS3-Codec [51] have been investigated for efficient modeling. Recently, finite scalar quantization (FSQ)-based models [1, 39] have been adopted to improve the performance of low-bitrate neural audio codec. CosyVoice 2 [8] introduces supervised semantic tokens and flow matching with causal layer and lookahead tokens.

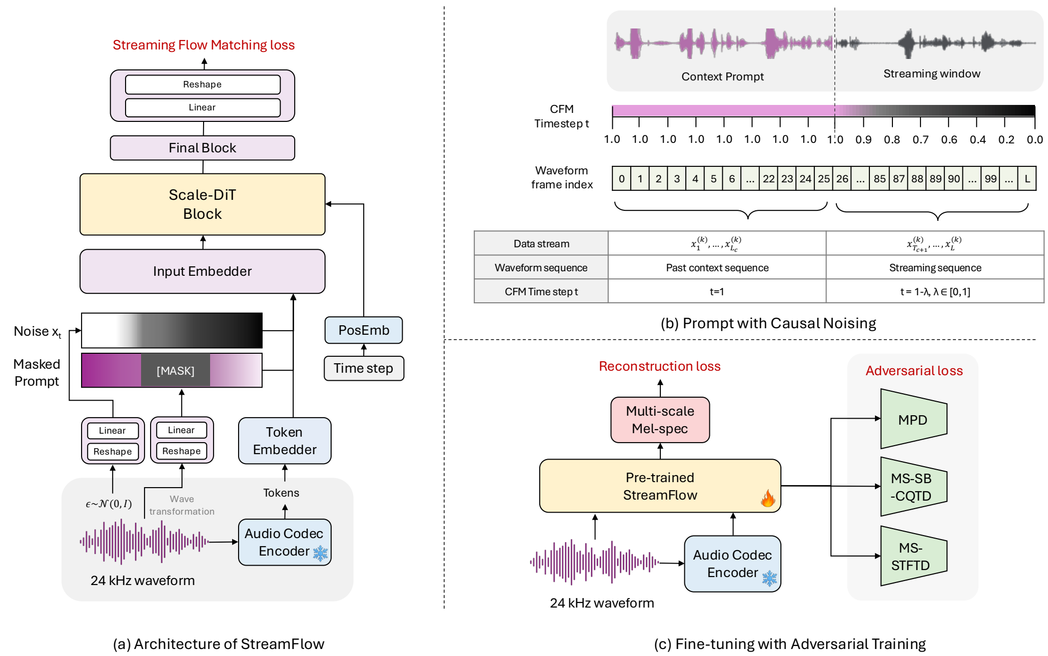


Figure 3: The Overall framework of StreamFlow.

2.4 Full-Duplex Real-time Speech Language Models

Recent advances in speech foundation models [7, 3] have introduced full-duplex systems capable of simultaneous speech input and output in real-time. Achieving this requires both low-latency streaming architectures and highly efficient low-bitrate neural codecs. A common design pattern involves causal convolution-based decoders for real-time waveform generation. However, such causal models generally underperform compared to their parallel counterparts in terms of perceptual quality. Moreover, the reliance on low-bitrate codecs, while necessary for efficient streaming, often introduces noticeable degradation in audio quality and fidelity. To address these limitations, we propose SFM, a method that enables high-fidelity, low-latency waveform generation—bridging the gap between efficiency and perceptual quality in streaming audio generation, as illustrated in Figure 2-(b).

3 StreamFlow

This section introduces the StreamFlow framework for high-quality real-time audio streaming generation. We begin with the fundamentals of Flow Matching (Section 3.1) and extend it to an efficient Streaming Flow Matching method (Section 3.2). We then describe the data stream, causal noising, training objective, and streaming generation process. Next, we present Scale-DiT for improved contextual learning and generalization (Section 3.3), and explore waveform transformation for efficient streaming generation (Section 3.4). Finally, we discuss adversarial training for enhanced robustness and efficiency (Section 3.5).

3.1 Preliminary: Flow Matching

Flow Matching (FM) [31, 33, 48] is a generative modeling method designed to transform a simple prior distribution $p_0(x)$ (e.g., $x_0 \sim \mathcal{N}(0, I)$) into a target data distribution $p_1(x) \approx q(x)$ by learning a time-dependent velocity field $v_t(x)$. This transformation is governed by the following ordinary differential equation (ODE):

$$\frac{d\phi_t(x)}{dt} = v_t(\phi_t(x); \theta), \quad \phi_0(x) = x, \, x \sim p_0, \tag{1}$$

where $\phi_t(x)$ represents the state of the system at time t as it evolves under the velocity field v_t. The FM objective aims to align the learned velocity field $v_t(x;\theta)$ with an ideal vector field $u_t(x)$ that generates the desired probability path $p_t(x)$. This alignment is achieved by minimizing the following training objective:

$$L_{\text{FM}}(\theta) = \mathbb{E}_{t\sim[0,1],x\sim p_t(x)} \left\| v_t(x;\theta) - u_t(x) \right\|^2 . \tag{2}$$

To define the probability path $p_t(x)$, a common approach is to employ linear interpolation between the prior sample x_0 and the target data point x_1:

$$x_t = (1-t)x_0 + tx_1. \tag{3}$$

The corresponding ideal vector field $u_t(x_t \mid x_1)$ that drives the transformation along this path is given by:

$$u_t(x_t \mid x_1) = x_1 - x_0. \tag{4}$$

This method effectively learns a smooth and computationally efficient mapping from p_0 to p_1.

3.2 Streaming Flow Matching

We introduce Streaming Flow Matching (SFM), a novel approach designed for real-time streaming inference by simultaneously estimating multi-time vector fields. Unlike traditional FM, which processes entire sequences simultaneously, SFM utilizes dynamically structured streaming sequences and jointly optimizes local and global vector fields. Notably, by estimating multiple vector fields across multiple time axes, SFM provides not only the global consistency inherited from classical FM but also satisfies real-time constraints in streaming scenarios.

Data Streams SFM partitions the input sequence $\mathbf{x}$ into multiple data streams, each characterized by a streaming window size L_{s} and a context prompt ratio γ. The total length is thus $L = L_{\text{c}} + L_{\text{s}}$, where $L_{\text{c}} = \gamma \cdot L_{\text{s}}$. Specifically, each data stream $\{\mathbf{x}_1^{(k)}, \ldots, \mathbf{x}_L^{(k)}\}$ simultaneously provides contextual information (i.e., the context prompt) and performs streaming inference (i.e., the streaming window). To achieve this, SFM defines two separate timestep sequences. The first sequences corresponds to the past context segment, which remains fixed at $t = 1$. The second sequences handles the streaming segment, where t decreases linearly as $t = 1 - \lambda, \lambda \in [0, 1]$ along to the L_s.

Causal Noising To ensure causality, the SFM introduces the causal noising technique, selectively masking the streaming window while retaining context prompt for in-context learning. This approach imposes temporal constraints, preventing information leakage from future data. For each stream k, let the initial state $\mathbf{x}_0^{(k)}$ follow a Gaussian distribution $\mathcal{N}(0, I)$, and let $\mathbf{x}_1^{(k)}$ be the target data point. Then, the following interpolation path is defined for $t \in [0, 1]$:

$$\mathbf{x}_t^{(k)} \;=\; (1-t)\,\mathbf{x}_0^{(k)} \;+\; t\,\mathbf{x}_1^{(k)}. \tag{5}$$

Within this path, the streaming window is monotonically reduced from $t = 1$ to 0, effectively reducing the range of actively learned stream. The context prompt, however, remains fixed throughout training, ensuring that the model retains past context information while progressively refining the newly generated output. In a streaming scenario, the context prompt is dynamically updated to integrate newly generated frames while preserving historical context. Meanwhile, the model iteratively refines its predictions through causal noising, wherein structured noise is introduced at each step and progressively reduced over time. Furthermore, newly generated frames are incorporated via a causal shift operation, ensuring a smooth transition between past and present content. As a result, this process not only preserves temporal coherence and stabilizes streaming generation but also prevents information leakage and enhances robustness.

Training Objective The training objective of SFM is to predict the ideal velocity field $\mathbf{u}_t^{(k)}$. This velocity field is derived via the temporal derivative of the interpolated path $\mathbf{x}_t^{(k)}$, which simplifies to

$$\mathbf{u}_t^{(k)} \;=\; \frac{d\,\mathbf{x}_t^{(k)}}{dt} \;=\; \mathbf{x}_1^{(k)} - \mathbf{x}_0^{(k)}. \tag{6}$$

We define the following loss function to minimize the difference between the predicted $\mathbf{v}_t^{(k)}(\theta)$ and the ideal $\mathbf{u}_t^{(k)}$:

$$L_{\text{SFM}}(\theta) = \sum_{k=1}^{K} \mathbb{E}_{t,\mathbf{x}_0^{(k)},\mathbf{x}_1^{(k)}} \left[\left\| \mathbf{v}_t^{(k)}\left(\tilde{\mathbf{x}}_t^{(k)}; \mathbf{c}^{(k-1)}; \theta\right) - \left(\mathbf{x}_1^{(k)} - \mathbf{x}_0^{(k)}\right) \right\|^2 \right], \tag{7}$$

where $\tilde{\mathbf{x}}_t^{(k)}$ is the causally noised interpolation state, $\mathbf{c}^{(k-1)}$ represents context prompt providing temporal consistency and in-context streaming generation ability.

Streaming Generation Thanks to in-context learning ability of Transformer, the model can learn the long-term dependency during streaming generation. To emerge this ability, we train the model by applying causal noising to the data stream, and estimating the multi-time vector fields at once according to the level of noising. Following [24], we also utilize condition drop for prompt and tokens during training. During inference, we prepend the generated samples at the front of the sequence as a prompt to in-context learn from the generated data. Furthermore, $\mathbf{x}_t$ can be refined by reflecting the next token stream during generation.

3.3 Scale-DiT

Inspired by [34], we introduce Scale-DiT, a novel architecture designed to enhance training stability and improve model performance. We aim to preserve the scalability of existing DiT while addressing limitations in optimization and feature representation. This approach allows the model to regulate feature more effectively during training, leading to more stable optimization within Multi-Head Self-Attention (MHSA) and Feed-Forward Network (FFN) layers. Specifically, Adaptive Layer Normalization (AdaLN) is integrated with a dynamic scaling mechanism to regularize the feature space effectively. Given an input sequence $x \in \mathbb{R}$, we first apply AdaLN to obtain a normalized representation $\hat{x}$ along with trainable scaling and shifting parameters $\gamma_1, \beta_1, \gamma_2, \beta_2$, and gating factors α_1, α_2. The MHSA output is computed as:

$$\hat{x} = \sigma(x) \cdot (1 + \gamma_1) + \beta_1, \tag{8}$$

where $\sigma(\cdot)$ denotes the layer normalization (LN) function.

$$\mathbf{A} = \alpha_1 \cdot \text{MHSA}(\hat{x}). \tag{9}$$

Unlike vanilla DiT residual connections, we introduce an learnable adaptive scaling rate ρ_1, which is restricted between 10^{-4} and 1 before applying it for robust training. This adaptive rate modulates the residual update with the difference:

$$x \leftarrow x + \rho_1 \cdot \sigma(\mathbf{A} - x), \tag{10}$$

where we utilize additional LN, ensuring controlled information flow and stable optimization for the difference. Following the MHSA computation, we apply an AdaLN as:

$$\hat{x} = \sigma(x) \cdot (1 + \gamma_2) + \beta_2 \tag{11}$$

before passing it through the FFN, which is further scaled by α_2, leading to

$$\mathbf{F} = \alpha_2 \cdot \text{FFN}(\hat{x}). \tag{12}$$

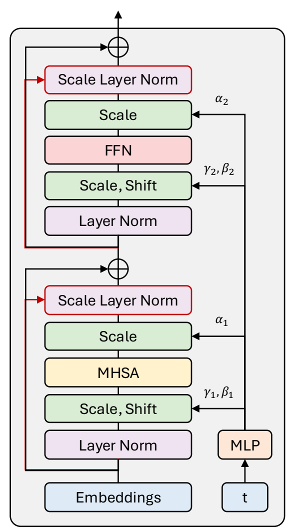


Figure 4: Scale-DiT architecture of StreamFlow.

To maintain training stability and prevent extreme gradient updates, we introduce a separate adaptive scaling rate ρ_2 for the FFN layer. Finally, the residual connection is updated as:

$$x \leftarrow x + \rho_2 \cdot \sigma(\mathbf{F} - x). \tag{13}$$

By scale layer normalization, Scale-DiT improves training stability, optimizes representation learning efficiency, and enhances overall optimization dynamics.

Table 1: Objective evaluation results from EnCodec tokens using universal speech test samples. RFWave uses CFG2.

Model	Streaming	Params.	M-STFT ↓	PESQ ↑	Period ↓	V/UV ↑	UTMOS ↑	MOS ↑
GT	-	-	-	-	-	-	3.423	4.07±0.02
Vocos [46]	✗	7M	1.074	3.051	0.086	0.957	3.100	3.98±0.02
MBD [13]	✗	411M	1.612	2.645	0.108	0.946	3.300	3.95±0.03
RFWave [32]	✗	18M	1.280	3.020	0.078	0.957	2.988	3.99±0.02
StreamFlow	✗	170M	0.997	3.473	0.080	0.957	3.450	4.03±0.02
Encodec [9]	✓	15M	1.170	2.643	0.112	0.941	2.542	3.74±0.03
StreamFlow-Tiny	✓	11M	1.111	3.027	0.107	0.947	3.060	3.99±0.02
StreamFlow-Small	✓	44M	1.072	3.207	0.096	0.950	3.206	3.99±0.03
StreamFlow-Base	✓	175M	1.061	3.335	0.102	0.948	3.325	4.03±0.02

3.4 Waveform Transformation

STFT/iSTFT Conventional waveform generation models used high-resolution features with transposed convolutional layer. However, increasing the resolution of features significantly increases the inference speed. Vocos [46] introduced iSTFT head to directly transform the feature into waveform signals on the low-resolution features. Unlike one-step generation models, we utilize multi-step generation frameworks using CFM so we first extract the STFT-based features of an input $\mathbf{x}_t$ and prompt and iSTFT-based vector field estimation. However, we found that STFT and iSTFT require additional computation cost for each sampling step, and larger receptive field (window size) than the quantization size of the token (hop size) so it is not proper for the streaming generation system because it is essential to use future tokens for robust waveform generation.

Linear-Reshape Transformation To reduce this problem, we adopt a linear reshape transformation proposed in WaveNeXt [36]. We first reshape the 1d waveform-level input $\mathbf{x}_t$ and prompt of length T into 2d data of height T/h and width h, where h denotes hop size like STFT. After reshaping the data, we apply the linear projection to map it into the feature space for Scale-DiT. For vector field prediction, we also utilize linear projection to the data space, and reshape 2d data into 1d original reshape for loss calculation. It is worth noting that it does not require additional future frames and reshape function during sampling steps unlike STFT-based models, resulting in better efficient and faster streaming generation. Specifically, we reshape the waveform signal by h of 160.[2]

3.5 Fine-tuning with Adversarial Training

For high-fidelity waveform generation, many works utilize adversarial training by introducing well-designed discriminators. Although leveraging multi-scale of various discriminator could improve the performance of waveform generation models, it requires too much time to train the models and it is difficult to optimize their losses together. To reduce the entire training time, we first train the StreamFlow using the proposed SFM objective, and fine-tune the pre-trained StreamFlow with adversarial training following [28]. For adversarial training, we utilized the multi-period discriminator (MPD) of HiFi-GAN [20] to reflect the different periodic features, multi-scale short time Fourier transform discriminator (MS-STFTD) of [9] to reflect the magnitude and phase from different STFTs, and multi-scale sub-band constant-Q transform (MS-SB-CQTD) of [13] to reflect the detailed frequency features. Furthermore, we also utilize multi-scale STFT losses of BigVGAN-v2 together.

4 Experiment and Result

4.1 Experimental Setup

Dataset We utilized LibriTTS [60] to train all models including the ablation study. LibriTTS is a high-quality speech dataset with a sampling rate of 24,000 Hz. We used EnCodec and Mimi

[2]We have compared the size of h at our preliminary study. Decreasing h could improve the performance but increase the computation complexity. We recommend decreasing the dimension size when using smaller h. This has the advantage of a smaller parameter size with similar performance.

Table 2: Ablation study on Streaming StreamFlow using the LibriTTS-dev subset.

Model	M-STFT ↓	PESQ ↑	Period ↓	V/UV ↑	Pitch ↓	UTMOS ↑
Streaming (online)						
StreamFlow	1.088	3.430	0.088	0.955	26.843	3.792
w/o In-Context Learning	1.099	3.337	0.088	0.954	26.772	3.748
w/o Adversarial Fine-tuning	1.388	2.669	0.101	0.950	21.099	3.178
w/o SFM Pre-training	1.919	1.153	0.353	0.812	574.55	1.308
w/o Scale-DiT	1.593	2.557	0.099	0.946	27.330	3.033
w/o RoPE	2.049	1.598	0.176	0.898	68.891	1.904
Non-streaming (offline)						
StreamFlow	1.017	3.499	0.085	0.955	29.087	3.888
w/o iSTFT	1.097	3.139	0.082	0.956	22.636	3.619

as speech tokenizers to compare the streaming reconstruction performance because they consist of causal convolutional layers for encoding and decoding the waveform signal. We utilize eight RVQ of each model to train the model.[3] We first validate the models using LibriTTS-dev clean and test subsets, and then we evaluate the performance of each model using universal speech datasets consisting of 300 samples from various datasets including Expresso, HiFiTTS, LibriTTS, Aishell3, JVS, and CML-TTS following RFWave [32].

Training For streaming models, we pre-train StreamFlow models with a learning rate of 2×10^{-4}, batch size of 512 for 1M steps on four NVIDIA A6000 GPUs. We utilize sliced window training by randomly segmenting the waveform signal by 10,240 frames (32 tokens of EnCodec). Then, we fine-tune StreamFlow with a learning rate of 2×10^{-5}, batch size of 64 for 0.25M steps on four NVIDIA A6000 GPUs. We utilize sliced window training by randomly segmenting the waveform signal by 20,480 frames (64 tokens of EnCodec). The architecture details are described in Appendix A. The parallel models are described in Appendix B.

Sampling We utilize the Euler method as the ODE method. We compared the sampling steps for pre-trained models in Table 9. For streaming models, we fine-tuned the model with the fixed-step generator by four steps of parallel models and eight steps of streaming models. For Mimi reconstruction, we fixed two steps for minimal latency.

4.2 EnCodec Token Reconstruction

We compared the performance of EnCodec token reconstruction with the strong parallel baselines including Vocos, Multi-Band Diffusion (MBD), and RFWave. Furthermore, we compare with the streaming baselines including causal EnCodec with the same latency to obtain robust streaming generation. Table 1 demonstrated the effectiveness of our methods in that streaming models still outperformed the powerful parallel models including MBD and RFWave. Furthermore, StreamFlow-T also shows better performance in terms of PESQ. This indicated that our new streaming generation frameworks could improve the streaming generation performance significantly. Table 1 shows that our models have much better performance in terms of MOS compared to previous streaming methods, and also better performance compared to parallel models.

4.3 Ablation Study

In-Context Learning When we prepend the generated samples as prompts, the models could learn useful information from them. Table 2 also showed much better performance than the model without prompt even with the same hyperparameter.

Adversarial Fine-tuning The results demonstrated the efficiency and effectiveness of two-stage training using SFM and adversarial training. Although we only fine-tuned the models with small training steps of 0.25M, the performance improved significantly.

[3] We found that StreamFlow using eight RVQ token embedding for training can still generate waveform signal from any number of RVQ token due to iterative refinement.

Table 3: Scalability with respect to model size

Model	Params.	Input Dim.	Hidden	Head	M-STFT ↓	PESQ ↑	Period ↓	V/UV ↑	Pitch ↓	UTMOS ↑
StreamFlow-Tiny	11M	256	1024	4	1.126	3.183	0.097	0.951	27.846	3.550
StreamFlow-Small	44M	512	2048	8	1.099	3.307	0.089	0.955	27.740	3.690
StreamFlow-Base	175M	1024	4096	16	1.088	3.430	0.088	0.955	26.843	3.792

Table 4: Additional comparison between DiT and Scale-DiT before adversarial fine-tuning. We use 16 steps of Euler method for sampling. Objective evaluation results from Mimi tokens using LibriTTS-dev subsets.

Model	Training Steps	WER ↓	STOI ↑	PESQ ↑	SPK-SIM ↑	UTMOS ↑
DiT	150k	11.76	0.85	1.71	0.58	2.72
DiT + REPA	150k	8.76	0.86	1.74	0.59	2.85
Scale-DiT	150k	9.68	0.86	1.78	0.59	2.83
Scale-DiT + REPA	150k	8.34	0.87	1.78	0.60	2.92
DiT	300k	9.41	0.87	1.84	0.62	3.04
DiT + REPA	300k	8.17	0.87	1.84	0.64	3.10
Scale-DiT	300k	7.56	0.87	1.90	0.64	3.16
Scale-DiT + REPA	300k	7.18	0.88	1.92	0.65	3.26
DiT	700k	9.59	0.87	1.92	0.64	3.20
DiT + REPA	700k	6.88	0.88	1.92	0.67	3.28
Scale-DiT	700k	6.23	0.88	2.07	0.68	3.45
Scale-DiT + REPA	700k	5.99	0.89	2.09	0.68	3.52

SFM Pre-training Without SFM pre-training, the model with adversarial training could not emerge streaming generation ability with ODE sampling at the early steps, resulting in discriminator collapse and slow training speed.

Scale-DiT We found that training the vanilla DiT model with a linear-reshape transformation using a high-resolution waveform signal as a target is unstable. Compared to the vanilla DiT, Table 2 indicated that Scale-DiT could improve the performance. We also observed that the learning process exhibits increased stability with reduced fluctuations during training.

RoPE For streaming generation, it is essential to use positional embeddings. The model without RoPE could not generate the waveform signal well due to a lack of ability to learn the positional information of high-resolution waveform signal.

Linear-Reshape Transformation Table 2 confirmed that STFT/iSTFT-based models are better than Linear-Reshape transformation for parallel generation models so we used STFT/iSTFT-based methods for parallel models. However, as we described in section 3.4, STFT/iSTFT is not proper for streaming generation because it requires a larger receptive field for their transformation so we used Linear-Reshape transformation for streaming methods.

Scalability We train three different models as described in Table 3. The results demonstrate consistent scalability with respect to model size across all evaluation metrics.

4.4 Further Analysis of Scale-DiT

As a further analysis of Scale-DiT, we first compare it with the vanilla DiT baseline to investigate its effectiveness and stability. As shown in Table 4, Scale-DiT consistently achieves better performance across all evaluation metrics, demonstrating enhanced stability and stronger capability for hierarchical feature modeling. These improvements suggest that the proposed scaling mechanism effectively stabilizes training and optimizes feature representations compared to the vanilla DiT. Building upon these results, we conducted additional experiments to investigate whether Scale-DiT can be further enhanced through feature regularization. Specifically, we incorporated representation alignment for generation (REPA) [58] into the architecture to examine its extensibility and robustness. In this setting, the 7th-layer representation from Wav2Vec 2.0 was used as the target semantic embedding, replacing the DINOv2 features employed in the original REPA, and a cosine similarity based REPA loss was applied at the 6th block of our 12-block model. When combined with REPA (Scale-DiT + REPA), the model achieved additional gains indicating that Scale-DiT provides a solid and stable foundation for structured feature learning, while REPA serves as an effective auxiliary regularization technique for further refinement.

Table 5: Objective evaluation results from Mimi tokens using LibriTTS-dev subsets. Note that StreamFlow performs inference in a two-step process.

Model	N_q	Bitrate	F (Hz)	CER ↓	WER ↓	M-STFT ↓	PESQ ↑	Period. ↓	V/UV ↑	Pitch ↓	UTMOS ↑
GT	-	-	-	1.12	3.06	-	-	-	-	-	3.862
Mimi	4	550	50	7.42	12.72	1.552	1.657	0.210	0.880	77.575	3.019
StreamFlow	4	550	50	5.22	9.45	1.410	1.584	0.212	0.876	73.891	3.093
Mimi	6	825	75	5.10	9.00	1.426	2.012	0.180	0.901	60.142	3.347
StreamFlow	6	825	75	3.78	6.87	1.272	2.043	0.177	0.906	55.830	3.719
Mimi	8	1100	100	3.05	6.93	1.352	2.266	0.165	0.910	50.686	3.506
StreamFlow	8	1100	100	3.26	6.16	1.217	2.306	0.162	0.915	45.640	3.910

Table 6: Inference details and subjective evaluation results from Mimi tokens using universal speech test samples. Note that StreamFlow performs inference in a two-step process.

Model	N_q	Bitrate	F (Hz)	Params.	Latency ↓	xRTF ↑	Avg. Memory ↓	CMOS ↑	UTMOS ↑
Mimi	4	550	50	79M	80ms	-	-	-	2.62
StreamFlow	4	550	50	175M	160ms	-	-	+0.058	2.76
Mimi	6	825	75	79M	80ms	-	-	-	2.91
StreamFlow	6	825	75	175M	160ms	-	-	+0.022	3.34
Mimi	8	1100	100	79M	80ms	3.224	502MB	-	3.06
StreamFlow	8	1100	100	175M	160ms	8.319	1176MB	+0.085	3.55

4.5 Mimi Token Reconstruction

We evaluated the Mimi decoder and StreamFlow on Mimi token reconstruction using LibriTTS-dev subsets and universal speech test samples. As detailed in Table 5, StreamFlow outperforms Mimi decoder in terms of WER, M-STFT, PESQ, Pitch, and UTMOS, and has a comparable performance in other metrics. Inference details and subjective scores are summarized in Table 6. Furthermore, StreamFlow directly generated high-resolution waveform signal on the low-resolution features by linear-reshape transformation, resulting in a much faster inference speed compared to the Mimi decoder. This indicates that our model could replace the Mimi decoder for full-duplex real-time speech language models of Moshi. We provide a detailed description of the system's operation in a full-duplex setting in Appendix H.

5 Potential Broader Impact

Practical Application We introduce a new generative model, streaming flow matching (SFM) for streaming generation, and a new diffusion architecture, Scale-DiT. This can be adopted for sequential data generation including video generation, audio generation, and stock prediction. We successfully leveraged our methods to real-time streaming waveform generation by proposing StreamFlow. This can accelerate the research of text-to-speech [27, 29], text-to-audio, real-time voice conversion [6], and speech language models with high-quality audio generation.

Limitation In this work, we focus real-time generation system using SFM. However, we observed that increasing the sampling steps of SFM can further improve the quality. Therefore, we aim to minimize the trade-off between real-time processing and quality even with more sampling steps. While SFM pre-training significantly reduces the overall training time and emerge new ability for streaming generation, adversarial fine-tuning is still required for high-fidelity waveform generation, resulting in slow training speed due to various discriminators.

6 Conclusion

We presented a novel steaming generative models, streaming flow matching (SFM) for real-time streaming generation. Additionally, we introduce Scale-DiT, a robust diffusion Transformers architecture. We verified the effectiveness of our proposed methods in real-time high-resolution waveform signal generation tasks. To achieve this, we carefully designed a new waveform generation model, StreamFlow, which incorporates SFM, Scale-DiT, and linear-reshape transformation for high-resolution waveform modeling using EnCodec and Mimi tokens. Furthermore, we demonstrated the scalability of our models, and we have a plan to train much larger models for better generalization. Additionally, we see that our methods can be applied to directly train the neural audio codec more efficiently.

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A Implementation Details for Streaming Models

We describe the hyperparameter details of StreamFlow for streaming models at Table 7. For EnCodec Token, we successfully train the model with small segment size. However, we found that extracting Mimi tokens with small segment size significantly decrease the performance because Mimi compressed waveform signal of 24,000 Hz into 12.5 Hz. In this regard, we pre-trained the StreamFlow-Mimi with larger segment size . Furthermore, we utilize small size of audio/token drop for Mimi model because we only utilized two-step generation. Due to the limited GPU resource, we only trained the StreamFlow-Mimi for 0.15M steps. However, our model shows much better performance than Mimi.

Table 7: Hyperparameters of StreamFlow for streaming EnCodec token reconstruction.

Module	Hyperparameter	SteamFlow-T	SteamFlow-S	SteamFlow-B	SteamFlow-Mimi
Time	Time Embedding	256	512	1024	1024
	Linear1	[256, 1024]	[512, 2048]	[1024, 4096]	[1024, 4096]
	Activation	SiLU	SiLU	SiLU	SiLU
	Linear2	[1024, 256]	[2048, 512]	[4096, 1024]	[4096, 1024]
Condition	Token	EnCodec	EnCodec	EnCodec	Mimi
	Token Hz	75 Hz	75 Hz	75 Hz	12.5Hz
	Frame per token	320	320	320	1920
	Token dim	128	128	128	512
	Linear1	[128, 256]	[128, 512]	[128, 1024]	[512, 1024]
	Activation1	GELU	GELU	GELU	GELU
	Linear2	[256, 256]	[512, 512]	[1024, 1024]	[1024, 1024]
	Activation2	GELU	GELU	GELU	GELU
	Upsampling	Repeating 2	Repeating 2	Repeating 2	Repeating 12
Input&Prompt Linear Reshape	h	160	160	160	160
	Linear1 (No Bias)	[160, 512]	[160,1024]	[160, 2048]	[160, 2048]
	Linear2	[512, 256]	[1024,512]	[2048, 1024]	[2048, 1024]
Output Linear Reshape	Linear1	[256, 512]	[512,1024,]	[1024,2048]	[1024,2048]
	Linear2 (No Bias)	[512,160]	[1024,160]	[2048,160]	[2048,160]
	h	160	160	160	160
Scale-DiT	Input Dim.	256	512	1024	1024
	Hidden Dim.	1024	2048	4096	4096
	Layer	8	8	8	8
	Head	4	8	16	16
	Stream Token	8	8	8	2
	Prompt Token	24	24	24	6
	Context Prompt Ratio γ	3	3	3	3
Pre-train	Training Step	1M	1M	1M	0.5M
	Learning Rate	2×10^{-4}	2×10^{-4}	2×10^{-4}	2×10^{-4}
	Learning Scheduling	-	-	-	-
	Batch Size	512	512	512	128
	GPUs	4	4	4	4
	Noise Scale	0.25	0.25	0.25	0.25
	Segment Size	10240	10240	10240	48000
	Audio Drop	0.3	0.3	0.3	0.3
	Token Drop	0.2	0.2	0.2	0.2
Fine-tuning	Training Step	0.25M	0.25M	0.25M	0.15M
	Learning Rate	2×10^{-5}	2×10^{-5}	2×10^{-5}	2×10^{-5}
	Learning Scheduling	-	-	-	-
	Batch Size	64	64	64	64
	GPUs	4	4	4	4
	Noise Scale	0.25	0.25	0.25	0.25
	Segment Size	20480	20480	20480	30720
	Audio Drop	0.3	0.3	0.3	0.1
	Token Drop	0.2	0.2	0.2	0.1

B Implementation Details for Parallel Models

We describe the hyperparameter details of StreamFlow for parallel models at Table 8. We replace the linear-reshape transformation with STFT and iSTFT. We do not utilize any iSTFT head which was used in Vocos. We can not train the model with iSTFT head of Vocos during pre-training. We directly project components for iSTFT.

Table 8: Hyperparameters of StreamFlow for parallel EnCodec token reconstruction.

Module	Hyperparameter	SteamFlow + iSTFT	SteamFlow
Time	Time Embedding	1024	1024
	Linear1	[1024, 4096]	[1024, 4096]
	Activation	SiLU	SiLU
	Linear2	[4096, 1024]	[4096, 1024]
Condition	Token	EnCodec	EnCodec
	Token Hz	75 Hz	75 Hz
	Frame per token	320	320
	Token dim	128	128
	Linear1	[128, 1024]	[512, 1024]
	Activation1	GELU	GELU
	Linear2	[1024, 1024]	[1024, 1024]
	Activation2	GELU	GELU
	Upsampling	Repeating 2	Repeating 2
Input&Prompt Linear Reshape	h	-	160
	Linear1 (No Bias)	-	[160, 2048]
	Linear2	-	[2048, 1024]
Output Linear Reshape	Linear1	-	[1024,2048]
	Linear2 (No Bias)	-	[2048,160]
	h	-	160
STFT/iSTFT	Hop/Window/FFT	160/640/640	-
Scale-DiT	Input Dim.	1024	1024
	Hidden Dim.	4096	4096
	Layer	8	8
	Head	16	16
Pre-train	Training Step	1M	1M
	Learning Rate	2×10^{-4}	2×10^{-4}
	Learning Scheduling	-	-
	Batch Size	128	128
	GPUs	4	4
	Noise Scale	0.25	0.25
	Segment Size	48000	48000
	Audio Drop	0.3	0.3
	Token Drop	0.2	0.2
Fine-tuning	Training Step	0.25M	0.25M
	Learning Rate	2×10^{-5}	2×10^{-5}
	Learning Scheduling	-	-
	Batch Size	32	32
	GPUs	4	4
	Noise Scale	0.25	0.25
	Segment Size	48000	48000
	Audio Drop	0.3	0.3
	Token Drop	0.2	0.2

C Additional Experiments on Pre-trained StreamFlow

Table 9 provides additional objective evalutation results of the pre-trained StreamFlow on the LibriTTS-dev dataset without adversarial fine-tuning. We evaluate both non-streaming with different sampling steps and classifier-free guidance values. Notably, comparable performance to the 16-step setting is achieved even with only 4 sampling steps, demonstrating the efficiency in both offline and streaming scenarios.

Table 9: Objective Evaluation for the pre-trained StreamFlow without adversarial fine-tuning on the LibriTTS-dev subsets.

Model	Sampling Steps	CFG	M-STFT ↓	PESQ ↑	Period. ↓	V/UV ↑	Pitch ↓	UTMOS ↑
EnCodec	1	-	1.163	2.771	0.113	0.941	32.147	2.969
Non-streaming (offline)								
StreamFlow + iSTFT	16	1	1.301	3.094	0.087	0.953	28.635	3.450
StreamFlow + iSTFT	16	0.5	1.311	3.143	0.085	0.954	26.535	3.539
StreamFlow + iSTFT	16	0	1.399	2.827	0.094	0.950	27.020	3.482
StreamFlow + iSTFT	4	1	1.558	2.617	0.092	0.950	26.674	3.238
StreamFlow + iSTFT	4	0.5	1.561	2.668	0.089	0.952	27.905	3.339
StreamFlow + iSTFT	4	0	1.649	2.450	0.094	0.950	27.940	3.320
Streaming (online)								
StreamFlow	16	1	1.343	2.719	0.097	0.949	22.096	3.147
StreamFlow	16	0.5	1.341	2.790	0.093	0.952	20.328	3.224
StreamFlow	16	0	1.388	2.669	0.101	0.950	21.099	3.178
StreamFlow	4	1	1.509	2.479	0.101	0.946	20.956	3.012
StreamFlow	4	0.5	1.504	2.607	0.094	0.952	17.812	3.131
StreamFlow	4	0	1.570	2.557	0.095	0.952	18.697	3.149

D Implementation Details for Baselines

EnCodec We utilize an official implementation of EnCodec [9], which is the popular neural audio codec using RVQ and adversarial training.[4] They utilize causal convolutional layer for streaming application, and train the model with 32 quantizer of RVQ. However, most application utilized eight quantizer as target tokens so we train the model with eight tokens to reconstruct the waveform signal.

Vocos We utilize an official implementation of Vocos [46], which is an iSTFT-based waveform generation model with adversarial training.[5] They utilize an EnCodec as an input representation to reconstruct the waveform signal. We also generate the waveform signal by chunk-wise generation using Vocos to compare the streaming generation performance. For a fair comparision, we utilize the same previous and delayed tokens for chunk-wise generation for robust generation of Vocos.

MBD We utilize an official implementation of Multi-band Diffusion (MBD) [45] as a strong baseline for EnCodec token reconstruction.[6] MBD consists of four models for each band, and has large-scale parameters of 411M. Then, they utilize 10 sampling steps for each band so it takes a lot of time to generate the waveform signal even with parallel generation.

RFWave We utilize an official implementation of RFWave [32], which a strong baseline using conditional flow matching for multi-band parallel generation.[7] We utilize 20 sampling steps for better performance and CFG of 2 which is suggested by official implementation.

Mimi We utilize an official implementation of Mimi[8] from Moshi [7]. They utilize causal convolutional layer for streaming generation, and train the model with 32 quantizer of RVQ and compressed high-resolution waveform signal of 24,000 Hz into 12.5 Hz for efficient speech language models. Moshi only utilizes eight quantizer of RVQ for target tokens by delayed prediction so we also train the model with eight tokens.

[4] https://github.com/facebookresearch/encodec

[5] https://github.com/gemelo-ai/vocos

[6] https://github.com/facebookresearch/audiocraft

[7] https://github.com/bfs18/rfwave

[8] https://github.com/kyutai-labs/moshi

E Societal Negative Impact

Although our method and model do not directly contribute to malicious use or ethical concerns, they can be misused when combinded with text-to-speech or voice conversion models to deceive people. Therefore, it is crucial to explore fake audio detection and voice phishing detection models alongside our research. In the future, we aim to develop speech language models capable of identifying fake audio based on its content.

F Evaluation Details

M-STFT We employed the multi-resolution Short-Time Fourier Transform (M-STFT) distance implemented in the open-source Auraloss [47].[9] Originally proposed in Parallel WaveGAN [54], the M-STFT quantifies the distances between ground-truth and generated audio samples across multiple STFT resolutions, thereby capturing both fine and coarse spectral details.

PESQ For evaluating reproduction quality, we utilized the wide-band (WB) Perceptual Evaluation of Speech Quality (PESQ) metric [10]. The audio signals were downsampled to a sampling rate of 16,000 Hz before calculating the PESQ scores to ensure consistency with standard evaluation protocols. Furthermore, we normalize the downsampled waveform signal to avoid overflow.

Periodicity, V/UV F1, and Pitch Following the observations of CarGAN [35] regarding the perceptual degradation caused by periodicity artifacts, we measured periodicity errors using the Periodicity Root Mean Square Error (RMSE)[11]. Additionally, we evaluated the Voice/Unvoice (V/UV) classification performance using the F1 score to assess the accuracy of voiced and unvoiced regions in the generated audio. Also, we calculated pitch errors using the pitch Root Mean Square Error (RMSQ). All metrics utilize pitch predicted by CREPE [17]. We used the pytorch implementation of CREPE.[12]

UTMOS To assess the naturalness of the generated samples, we utilized the open-source Mean Opinion Score (MOS) prediction model, UTMOS [44].[13] UTMOS has demonstrated consistent MOS prediction performance on neutral English speech datasets, providing a reliable measure of the perceived naturalness of the synthesized audio without reference samples.

[9] https://github.com/csteinmetz1/auraloss
[10] https://github.com/ludlows/PESQ
[11] https://github.com/descriptinc/cargan
[12] https://github.com/maxrmorrison/torchcrepe
[13] https://github.com/tarepan/SpeechMOS

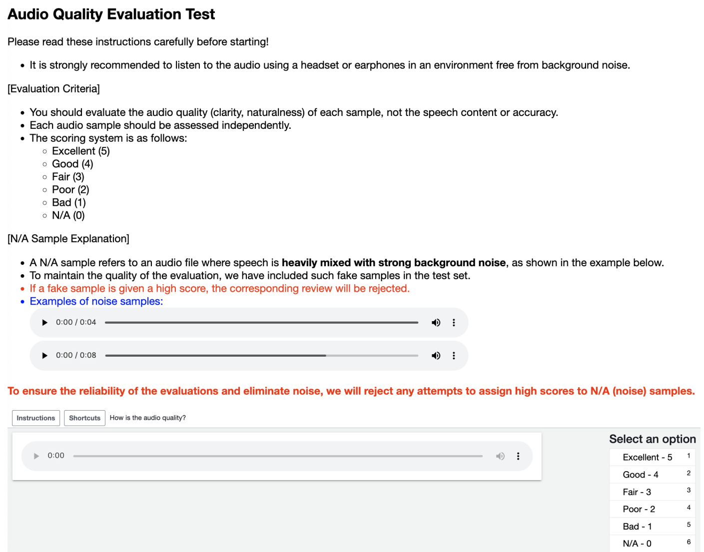

Figure 5: Details of the MOS evaluation interface provided to crowdsourcing participants

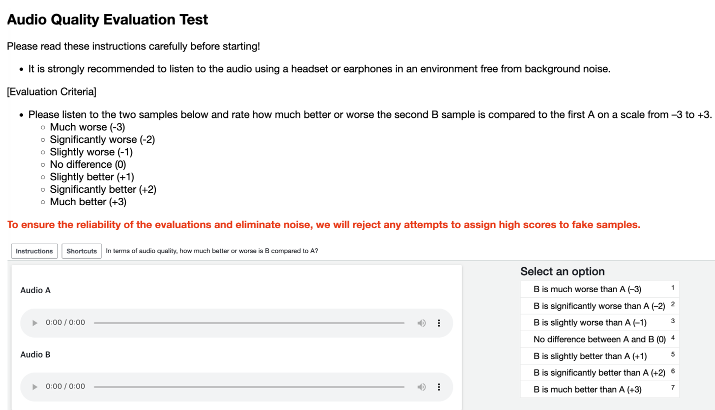

Figure 6: Details of the CMOS evaluation interface provided to crowdsourcing participants

G Crowdsourcing Details

We conducted Mean Opinion Score (MOS) evaluations using a 5-point scale to assess the quality of speech. The perceptual quality of each model was evaluated through a crowdsourced listening test using Amazon Mechanical Turk (MTurk)[14]. A total of 20 native English speakers from the United States participated, each rating 300 samples per model on a scale from 1 to 5. We paid $180 for each MOS experiment. To ensure the reliability of responses, we established strict participant eligibility criteria: only individuals with a prior task approval rate of at least 50% and a minimum of 100 approved HITs were permitted to take part in this evaluation. Additionally, we included Gaussian noise fake samples as control samples to enhance evaluation robustness, and we give the instruction which noise samples should be assigned as N/A sample (0 point). Listener responses were excluded from the final analysis if they met either of the following conditions: (1) assigning a score over 1 to the noise augmented samples, or (2) spending less than half the duration of an audio sample on the evaluation. These measures were implemented to filter out inattentive participants and maintain the integrity of the collected ratings. The user interface used for the evaluation is illustrated in Figure 5 and Figure 6.

[14] https://www.mturk.com/

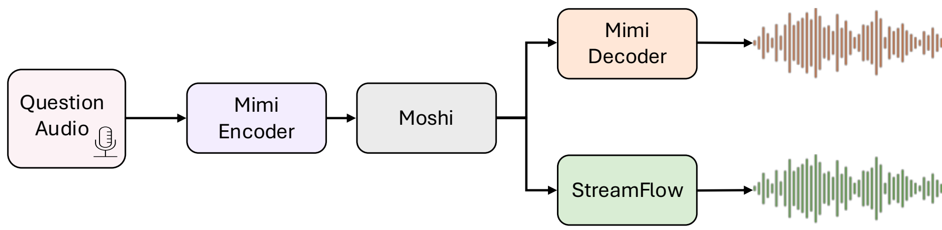

Figure 7: Inference pipeline comparing the Mimi decoder and the proposed StreamFlow, given identical Moshi output.

Table 10: Comparison of real-time decoding performance for full duplex spoken dialogue system, Moshi using the Mimi decoder and the proposed StreamFlow

Method	CER ↓	WER ↓	UTMOS ↑
Moshi w/ Mimi decoder	7.59	9.89	3.610
Moshi w/ StreamFlow (Ours)	**7.19**	**9.82**	**3.847**

H Replacing Mimi with StreamFlow in a Full-duplex Streaming Model

We replaced the original Mimi decoder in Moshi with StreamFlow, successfully integrating it into Moshi's fully-duplex streaming speech language model. For this integration, we utilized the official Moshi code[15], and conducted experiments using question audio from HeySQuAD [52][16] dataset as input. We upsampled the dataset, originally at 16 kHz sampling rate, to 24 kHz using Librosa and used it as input to Moshi. The outputs of the Moshi were kept identical across all conditions, allowing for a controlled comparison between the original Mimi decoder and our streaming StreamFlow. We evaluated both speech quality and speech intelligibility, using UTMOS, CER, and WER respectively as metrics. As shown in Table 10, our proposed StreamFlow consistently outperformed the Mimi decoder.

As shown in Figure 7, the pipeline of [Question Audio → Mimi Encoder→ LLM → Selectable Decoder] demonstrates that improvements at the decoder stage can lead to substantial gains in speech generation quality. These experiments support the effectiveness of the proposed decoder in streaming-based speech generation scenarios and highlight its practical potential as a viable alternative to the original architecture.

[15] https://github.com/kyutai-labs/moshi/blob/main/moshi/moshi/run_inference.py
[16] https://huggingface.co/datasets/yijingwu/HeySQuAD_human

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