

PSLM: Parallel Generation of Text and Speech with LLMs for Low-Latency Spoken Dialogue Systems

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Abstract

Multimodal language models that process both text and speech have a potential for applications in spoken dialogue systems. However, current models face two major challenges in response generation latency: (1) generating a spoken response requires the prior generation of a written response, and (2) speech sequences are significantly longer than text sequences. This study addresses these issues by extending the input and output sequences of the language model to support the parallel generation of text and speech. Our experiments on spoken question answering tasks demonstrate that our approach improves latency while maintaining the quality of response content. Additionally, we show that latency can be further reduced by generating speech in multiple sequences. Demo samples are available at <https://rinnakk.github.io/research/publications/PSLM>.

1 Introduction

Spoken dialogue systems have been developed for many years to achieve natural human-computer interaction (McTear, 2002; Jokinen and McTear, 2009; Chen et al., 2017). Traditionally, these systems consist of several components: Automatic Speech Recognition (ASR), Response Generation (RG), and Text-to-Speech (TTS). Various methods for RG have been proposed with the advancements in Large Language Models (LLMs) (Wang et al., 2023a; Yi et al., 2024). More recently, the application of LLMs to ASR (e.g., Wang et al. 2023b; Hono et al. 2024; Fathullah et al. 2024) and TTS (Wang et al., 2023b; Hao et al., 2023) has attracted much attention, leading to the development of multimodal LLMs capable of end-to-end spoken language communication (Zhang et al., 2023; Nachmani et al., 2024).

Zhang et al. (2023) proposed SpeechGPT, an LLM that receives speech questions (SQ) as speech

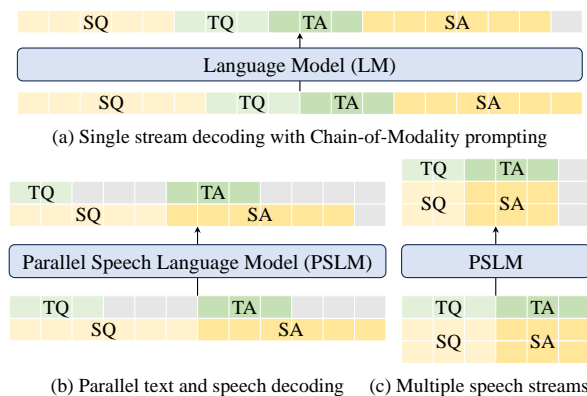


Figure 1: (a) Chain-of-Modality prompting necessitates generating text questions (TQ) and text answers (TA) from speech questions (SQ) before producing speech answers (SA). (b) Our Parallel Speech Language Model (PSLM) enables the parallel decoding of TA and SA, reducing overall latency. (c) Introducing multiple speech streams further accelerates the generation of SA.

tokens, which are discrete representations extracted from raw waveforms, and sequentially generates text questions (TQ), text answers (TA), and speech answers (SA). Figure 1 (a) illustrates their approach called Chain-of-Modality (CoM) prompting. Spectron (Nachmani et al., 2024) follows this prompting style but directly handles speech spectrograms. Although these methods can generate high-quality responses, they face two major challenges in terms of response latency. First, generating SA requires the prior generation of TQ and TA. Second, speech sequences are much longer than text sequences¹.

In this study, we propose Parallel Speech Language Model (PSLM), an LLM with multiple input-output sequences to handle both text and speech tokens, enabling their parallel generation. To emphasize their parallel processing capabilities, we will refer to these sequences as “streams”. As described in Figure 1 (b), PSLM begins to generate SA immediately after the end of SQ tokens,

¹Actual sequence lengths are provided in Appendix A.

which can reduce overall latency. This leads to our first research question (**RQ1**): Can PSLM improve latency while maintaining the response quality achieved by CoM prompting? Additionally, we address the second challenge by introducing multiple speech streams to decode multiple speech tokens in a single step, as described in Figure 1 (c). This brings us to the second research question (**RQ2**): Do multiple speech streams sacrifice the response quality? Addressing these questions will pave the way for more advanced and responsive applications of spoken dialogue systems.

2 PSLM

2.1 Speech Discretization

Speech Tokenization Extracting discrete speech tokens from raw waveforms enables language models to handle speech in the same manner as text tokens. Self-supervised learning has been widely used for speech tokenization due to its ability to extract spoken content from raw waveforms (e.g., Rubenstein et al. 2023; Chou et al. 2023; Hassid et al. 2023). Following Zhang et al. (2023), we employ Hidden-Unit BERT (HuBERT) (Hsu et al., 2021) for speech tokenization.

Speech Detokenization In contrast to text tokenization, which is uniquely recoverable, speech tokenization largely discards the information of raw waveforms. Two major approaches have been proposed to solve this problem. The first approach uses a neural vocoder for directly reconstructing raw waveforms from speech tokens (e.g., Zhang et al. 2023; Chou et al. 2023; Hassid et al. 2023). The second approach uses a pretrained neural audio codec, which requires an additional module to predict the codec’s tokens (e.g., Rubenstein et al. 2023; Zhang et al. 2024). We adopt the first approach to reduce overall latency using HiFi-GAN (Kong et al., 2020), a non-autoregressive neural vocoder that efficiently generates high-fidelity waveforms.

2.2 Integrating LMs with a Speech Stream

PSLM is built on top of a pretrained decoder-only Transformer (Vaswani et al., 2017). An overview of the PSLM architecture is provided in Figure 2. We add new input embedding and output projection layers to process speech tokens, while the structure of the intermediate Transformer layers remains unchanged. The embeddings of text and speech tokens are summed before being fed to the Transformer layers. The hidden features from the

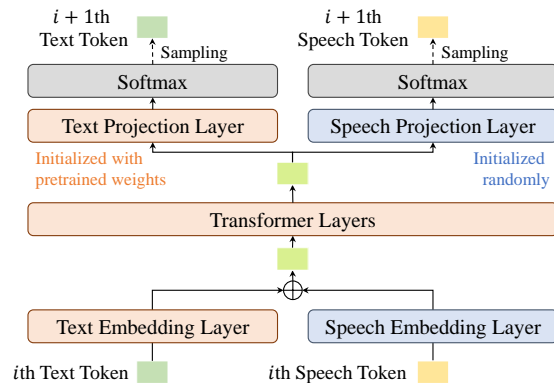


Figure 2: Architecture of PSLM.

final Transformer layer are passed to two output projection layers to calculate the logits of the next text and speech tokens. We randomly initialize the weights of new embedding and projection layers.

A challenge of joint text-speech modeling lies in the mismatch in their lengths. In this study, we simply right-pad TQ and TA sequences with special [TEXT-PAD] tokens to align their lengths with those of the SQ and SA sequences, respectively. In a preliminary experiment on the CoM-based architecture, we attempted to generate text tokens and their corresponding speech tokens alternatively in a similar manner to ELLA-V (Song et al., 2024); however, this approach led to frequent mispronunciation. This is mainly because, in our case, the text is represented by tokens rather than phonemes; in some languages, the pronunciation of a character often changes according to subsequent characters, and a certain amount of lookahead is necessary to achieve accurate pronunciation. In contrast, our alignment strategy allows the model to focus on text token generation initially and then refer to the generated text when producing the majority of speech tokens, leading to more accurate pronunciation.

Our PSLM is trained by minimizing the sum of cross entropy losses for each stream. We include prompt tokens, comprising TQ and SQ, in the loss calculation. During inference, PSLM receives these prompt tokens and generates TA and SA in parallel. Text and speech tokens are sampled independently from their respective distributions.

2.3 Introducing Multiple Speech Streams

For further acceleration, we introduce multiple speech streams to PSLM. Assume that PSLM has $1 + S$ streams, one for text tokens and S for speech tokens. Given the original speech token sequence of length N , the s -th speech stream consists of the

speech tokens with indices $s, s + S, s + 2S, \dots, s + MS$, where $s \in \{1, \dots, S\}$ and $M = \lfloor N/S \rfloor - 1$. Compared to simply increasing the batch size, where the system’s throughput improves but the latency for each instance remains unchanged, our approach reduces the sequence length handled by the Transformer layers to $1/S$, leading to an approximate S -fold speedup even in the single-instance scenario.

During training, simply summing the cross entropy losses for each stream makes the loss of text tokens less dominant, leading to poor text generation quality. Therefore, we introduce a weighted loss, where we multiply the loss for speech streams by $1/S$ to balance the weight of losses for text and speech streams.

2.4 Streaming Inference with HiFi-GAN

Following [Chen et al. \(2022\)](#), we use HiFi-GAN for streaming inference; specifically, we provide partial speech tokens to generate waveform fragments. In this study, we use non-causal convolution to maintain high speech quality. Therefore, the first speech fragment can be generated once $N_{\text{offset}} = \lfloor R/2 \rfloor + 1$ tokens are decoded, where R denotes the receptive field of HiFi-GAN. Implementation details can be found in [Appendix B](#).

2.5 Overall Latency

We define latency as the delay between the end of the user’s utterance and the system’s initial response. The latency of conventional CoM-based systems L_{CoM} can be represented as follows:

$$L_{\text{CoM}} = D_{s2t} + D_{\text{SQ}} + \frac{N_{\text{dec}}}{P} + D_{t2s} \quad (1)$$

$$N_{\text{dec}} = N_{\text{TQ}} + N_{\text{TA}} + N_{\text{offset}} \quad (2)$$

where D_{s2t} , D_{SQ} , and D_{t2s} denote the delays of speech tokenization, the prefill phase in LMs, and speech detokenization, respectively; N_{TQ} and N_{TA} denote the number of tokens in TQ and TA, respectively; and P denotes the tokens per second (TPS) during the decode phase in LMs.

Our PSLM eliminates the need for generating TQ and TA beforehand, although it requires to run external ASR to obtain TQ. Hence, its latency L_{PSLM} can be represented as follows:

$$L_{\text{PSLM}} = D_{\text{ASR}} + D_{\text{SQ}} + \frac{N_{\text{offset}}}{P \cdot S} + D_{t2s} \quad (3)$$

where D_{ASR} denotes the ASR delay. Here D_{s2t} is omitted because speech tokenization can be performed in parallel with ASR.

3 Experimental Setup

3.1 Dataset

We used an internal dataset comprising 1.8M written QA pairs for training all models. Since some of these samples, which were primarily crawled from the internet, were deemed unsuitable for evaluation, we used a publicly available Japanese dataset ([Hayashibe, 2023](#)) for evaluation. This dataset was manually reviewed and consists of 669 diverse written QA pairs. We further filtered the evaluation set by excluding samples whose TQ or TA exceeded 140 characters, the maximum number of characters observed in the training set. The final evaluation set contained 396 samples. For both the training and evaluation sets, we constructed a spoken question answering (SQA) dataset by synthesizing SQ and SA using a well-trained single-speaker TTS system based on VITS ([Kim et al., 2021](#)).

3.2 Configuration

Tokenization and Detokenization For text tokenization, we used the tokenizer with a vocabulary size of 151,936 from [rinna/nekomata-7b](#)². For speech tokenization, we applied k -means clustering with $k = 512$ to 12-th layer features from [rinna/japanese-hubert-base](#)³ ([Sawada et al., 2024](#)), obtaining 50 speech tokens per second. For speech detokenization, we trained discrete unit-based HiFi-GAN ([Polyak et al., 2021](#)) using pairs of synthesized speech waveforms of SQ and SA and their corresponding speech tokens. For ASR, Whisper large-v3 ([Radford et al., 2023](#)) with faster-whisper⁴ was used throughout our experiments.

Language Modeling We used [rinna/nekomata-7b](#), a 32-layer 4096-hidden-size Transformer LM that was continuously pretrained from Qwen-7B ([Bai et al., 2023](#)) on Japanese text, as the backbone of our models. We implemented our models using the GPT-NeoX library ([Andonian et al., 2023](#)). Unless otherwise noted, models were trained for 50k steps with a batch size of 16 on 8 NVIDIA A100 GPUs using an Adam optimizer ([Kingma and Ba, 2015](#)) with a peak learning rate set to $1e-5$. During inference, we set the temperature to 0.8 and applied top- k and top- p sampling with $k = 60$ and $p = 0.8$.

²<https://huggingface.co/rinna/nekomata-7b>

³<https://huggingface.co/rinna/japanese-hubert-base>

⁴<https://github.com/SYSTRAN/faster-whisper>

3.3 Baselines

We involved three CoM-based baselines, which share the model weights but differ in their prompts during decoding: (1) CoM-SQ receives only SQ, (2) CoM-ASR receives SQ and transcribed TQ, and (3) CoM receives SQ and gold TQ. In our preliminary experiments, the three-stage training (Zhang et al., 2023) was not effective in our configuration; thus, we trained the model using the same configuration as described in Section 3.2.

3.4 Evaluation Metrics

ChatGPT Scores We used OpenAI’s GPT-3.5 Turbo API to evaluate response quality on a 5-point scale from 1 (bad) to 5 (excellent). The prompt is described in Appendix C. We report the scores for TA and the transcription of SA as T-score and S-score, respectively.

Character Error Rate (CER) We calculated the character error rate between the generated TA and the transcription of SA to assess their alignment.

Failure Rate (FR) We counted failure cases such as (1) no [EOS] token was generated before the total sequence length reached 2048, or (2) tokens were generated in the wrong modality, i.e., speech tokens in TQ and TA, or text tokens in SA.

Latency We simulated latency according to Equations 2 and 3 for each sample in the evaluation set, and reported the median values. We set $D_{s2t} = 0.05$, $D_{SQ} = 0.05$, $D_{ASR} = 0.2$, and $D_{t2s} = 0.01$ based on measurements taken on a single NVIDIA A100 GPU. For the TPS value P , the actual TPS varies depending on computing resources and optimization; 70 TPS was achieved with vLLM (Kwon et al., 2023) optimization, and 25 TPS without it. Meanwhile, for streaming inference with HiFi-GAN, LMs need to generate 50 speech tokens per second. Therefore, we set P to 50 in our simulations to match this requirement.

Human Rating We also conducted two subjective evaluations: one for text and the other for speech. In the text evaluation, we presented pairs of gold TQ and generated TA, and raters evaluated the naturalness of TA based on the same criteria used in the ChatGPT-based evaluation (Text Naturalness). In the speech evaluation, we presented gold SQ and generated SA successively, along with their TQ and TA, and asked the raters to evaluate (1) how natural the SA is as the speech of the

TA (Speech Naturalness), and (2) whether the response is fast enough (Speed Score). For better reproducibility, we provide the actual instruction used for speech evaluation in Appendix D. The duration of silence between SQ and SA was simulated in the manner described in Section 2.5, except for the Ground Truth where the silence duration was set to 200ms, the average turn-taking gap in human conversation (Levinson and Torreira, 2015). Scores were rated on a 5-point scale. Fifty samples were randomly chosen from the evaluation set, and twenty in-house workers rated twenty samples each.

4 Results and Discussion

4.1 Automatic Evaluation

Comparison with Baselines To answer RQ1, we compared the proposed method in two conditions, PSLM and PSLM-ASR, with the baselines described in Section 3.3. PSLM receives SQ and gold TQ, while PSLM-ASR receives SQ and transcribed TQ. Table 1 summarizes the results. When gold TQ was given, PSLM achieved comparable scores to CoM and significantly improved latency. A similar trend was observed under more practical conditions where gold TQ was not available (PSLM-ASR vs. CoM-ASR). However, their scores were lower than those with gold TQ, and CoM-SQ faced greater degradation. These results suggest that ASR performance is crucial for response quality, and CoM-SQ seems to have produced more ASR errors than Whisper. Nevertheless, we conclude that PSLM maintains the response quality of CoM (RQ1). We also found that PSLM-based methods achieved lower FRs than CoM-based ones. Each stream of PSLM is dedicated to a single modality, which could have reduced the failures in generation. Furthermore, methods other than CoM-SQ marked lower CERs than Ground Truth. From this result, we confirmed that both CoM and PSLM can generate appropriate SA corresponding to TA.

Multiple Speech Streams To answer RQ2, we trained PSLM variants with two (-2x) or three (-3x) speech streams⁵. PSLM-2x achieved comparable scores to PSLM, whereas PSLM-3x demonstrated significant degradation. From these results, we conclude that speech tokens can be decoded in up to two streams without quality degradation (RQ2). An ablation study can be found in Appendix E.

⁵PSLM-3x was trained with a batch size of 4 due to the increased number of parameters.

Table 1: Automatic evaluation results. T-score and S-score represent the ChatGPT-based score for TA and transcribed SA, respectively. FR denotes the failure rate. Latency values in parentheses represent inputs involving gold TQ.

Method	Input modality	Output Modality	T-score \uparrow	S-score \uparrow	FR \downarrow	CER \downarrow	Latency [s] \downarrow
Ground Truth	—	—	4.00 \pm 0.02	3.58 \pm 0.06	—	7.35	—
CoM	SQ \rightarrow TQ (Gold)	TA \rightarrow SA	3.50 \pm 0.09	3.27 \pm 0.09	12.12	6.28	(0.67)
PSLM	SQ, TQ (Gold)	TA, SA	3.50 \pm 0.08	3.22 \pm 0.09	5.05	5.25	(0.34)
CoM-SQ	SQ	TQ \rightarrow TA \rightarrow SA	3.12 \pm 0.11	2.94 \pm 0.10	15.91	7.83	1.03
CoM-ASR	SQ \rightarrow TQ (ASR)	TA \rightarrow SA	3.27 \pm 0.10	3.07 \pm 0.09	13.13	6.18	0.92
PSLM-ASR	SQ, TQ (ASR)	TA, SA	3.34 \pm 0.09	3.05 \pm 0.10	6.31	6.05	0.54
PSLM-2x	SQ, TQ (Gold)	TA, SA	3.50 \pm 0.08	3.20 \pm 0.09	4.29	6.39	(0.20)
PSLM-3x	SQ, TQ (Gold)	TA, SA	3.28 \pm 0.10	2.99 \pm 0.10	7.07	6.09	(0.15)

Table 2: Human evaluation results.

Method	Text \uparrow	Speech \uparrow	Speed \uparrow
Ground Truth	4.08 \pm 0.26	3.74 \pm 0.19	4.73 \pm 0.11
CoM-SQ	2.44 \pm 0.29	4.04 \pm 0.20	4.07 \pm 0.23
CoM-ASR	2.90 \pm 0.30	3.94 \pm 0.20	4.17 \pm 0.22
PSLM-ASR	3.08 \pm 0.27	4.08 \pm 0.20	4.57 \pm 0.13

4.2 Human Evaluation

Considering practical applicability to SQA, we manually evaluated three methods: CoM-SQ, CoM-ASR, and PSLM-ASR, which do not rely on gold TQ, along with Ground-Truth. Table 2 shows the results. The text response naturalness of PSLM-ASR was comparable to CoM-ASR and higher than CoM-SQ, which is consistent with the automatic evaluation results. For speech naturalness, all methods achieved higher scores than Ground-Truth. This result can be attributed to two reasons: (1) SA of Ground-Truth are synthetic speech, which may include errors in pronunciation, intonation, and pauses, and (2) SA of Ground-Truth are typically longer than those of other methods, incurring that one or two unnatural parts lowered the entire score. Nevertheless, we confirmed that our approach can generate natural and faithful speech responses. For response speed evaluation, PSLM-ASR achieved a significantly higher score than CoM-ASR and CoM-SQ. This finding verifies that the proposed method reduces latency both numerically and perceptibly. Detailed analysis can be found in the next subsection.

4.3 Detailed Latency Analysis

The sequence length of TA, or N_{TA} , is the most influential factor in overall latency of CoM-based systems, as TA must be generated before SA. Thus, we investigated the overall latency by varying N_{TA} . Figure 3 shows the results. Due to the need for prior generation of TA, the latency of CoM-SQ and CoM-ASR increases linearly as TA length in-

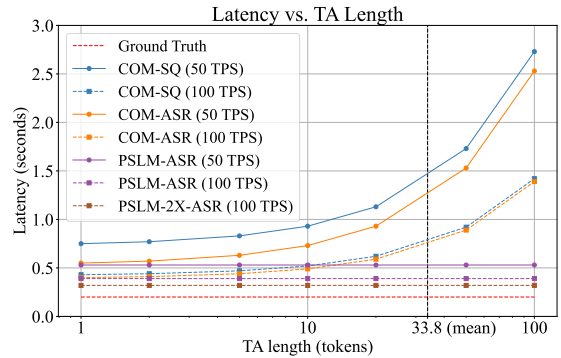


Figure 3: Latency vs. TA length for different methods and tokens per second (TPS). PSLM-2x-ASR (50 TPS) is omitted because its latency is identical to PSLM-ASR (100 TPS).

creases. In contrast, the latency of PSLM-ASR is constant because Equation 3 does not include N_{TA} , and PSLM-2x-ASR further reduces the latency. The gap between CoM-based and PSLM-based systems is remarkable when generating long TA, highlighting the effectiveness of generating text and speech tokens in parallel.

5 Conclusion

In this study, we proposed the Parallel Speech Language Model (PSLM), an LLM capable of generating text and speech tokens in parallel with multiple input-output streams, and investigated its impact on response quality and overall latency. The experimental evaluations on spoken question answering demonstrated that the proposed method significantly reduces latency compared to existing methods while maintaining response quality. Future work includes verifying the effectiveness of the proposed method on larger datasets and real speech data. Additionally, extending the proposed method to multi-turn dialogues is an important research direction.

6 Limitations

We recognize several limitations of this study. First, PSLM sacrifices ASR capability for faster response, requiring an external ASR module to serve as a spoken dialogue system. Although this dependency can complicate the system structure, it does not degrade the system’s performance, provided that an appropriate ASR module is selected. This is supported by the fact that CoM-ASR outperformed CoM-SQ, as described in Section 4.1. Nevertheless, enabling ASR with the PSLM architecture can be an interesting research direction. Second, we used single-speaker synthetic speech for SQ and SA, which lacks diversity in several aspects of speech such as accent, rhythm, emotion, and timbre. Practical applications may require to accept voices of arbitrary speakers, which we will address in future work. Finally, multi-turn dialogue settings were not investigated in our experiments. While SpeechGPT (Zhang et al., 2023) was not applied to multi-turn dialogue due to sequence length limitations, our models with multiple speech streams have the potential to perform multi-turn dialogue.

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A Sequence Length Distributions

We calculated the sequence length distributions of SQ, TQ, TA, and SA in the training set. The results are listed in Table 3. On average, CoM prompting requires to generate 36.5 (TQ) + 33.8 (TA) \approx 70 text tokens before generating SA. Eliminating the need for generating these tokens can greatly reduce overall latency. In addition, speech tokens are more than 11 times longer than text tokens, highlighting the need for efficient generation of speech tokens.

B Implementation Details of HiFi-GAN

The HiFi-GAN generator comprises convolution layers. Therefore, a waveform fragment corresponding to the i -th token depends only on tokens with indices $[i - \lfloor R/2 \rfloor, i + \lfloor R/2 \rfloor]$. This allows waveform generation to start before the entire SA is generated. As described in Figure 4, HiFi-GAN first generates a waveform fragment once the LM generates $N_{\text{offset}} = \lfloor R/2 \rfloor + 1$ tokens, then generates subsequent fragments by shifting input tokens one by one.

In our experiments, we trained HiFi-GAN to generate 24 kHz waveform from 50Hz tokens, which results in $R = 26$. Following Polyak et al. (2021), we embedded input speech tokens into 256-dimensional features and fed them to HiFi-GAN. We modified the upsampling rates to [8, 6, 5, 2], the number of total iterations to 300k, and kept the other configuration the same as the original work (Kong et al., 2020).

C ChatGPT Evaluation Prompt

We used the prompt in Figure 5 for ChatGPT-based evaluation. The original prompt was written in Japanese, but a translated version is presented here.

D Speech Evaluation Instruction

We used the instruction in Figure 6 for speech evaluation. The original instruction was written in Japanese, but a translated version is presented here.

E Ablation Study

We trained three PSLM variants, one from scratch (-no-pretrain), one without TQ (-no-TQ), and one without SQ (-no-SQ). In addition, we trained PSLM-2x and PSLM-3x without weighted loss (-no-WL). Table 4 shows the automatic evaluation results. PSLM-no-pretrain exhibited significant

Table 3: Sequence length distributions in the training set (in tokens).

	SQ	TQ	TA	SA
Mean	406.6	36.5	33.8	386.5
Min	34	2	1	27
25%	214	19	15	179
50%	354	32	29	340
75%	577	51	50	563
Max	1861	148	147	1697

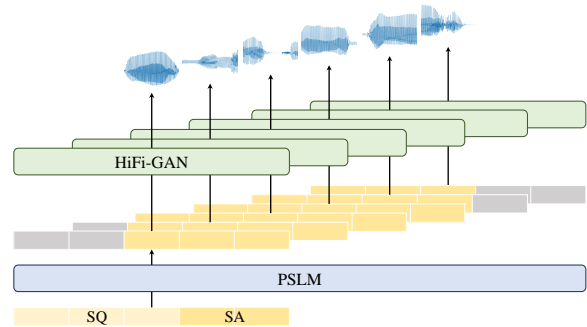


Figure 4: Streaming inference using HiFi-GAN with receptive field size $R = 5$ and SA length $N_{\text{SA}} = 6$. Waveform generation begins once $N_{\text{offset}} = \lfloor R/2 \rfloor + 1 = 3$ tokens are generated. Text tokens are omitted.

degradation in all metrics, indicating the necessity of pretrained LM’s text capability. PSLM-no-TQ also showed large degradation, highlighting the importance of TQ in response quality. In contrast, PSLM-no-SQ achieved comparable scores to PSLM. This result implies that the speech-specific information such as intonation, rhythm, and emotion is not essential in the current SQA task due to the use of synthetic speech. We also found that PSLM-2x-no-WL achieved almost comparable scores to PSLM, whereas PSLM-3x-no-WL showed significant degradation. From these results, we conclude that the weighted loss is especially effective as the number of speech streams increases.

A conversation between two individuals will be provided. The conversation follows a format where one asks a question and the other responds. Based on the following evaluation criteria, rate the response quality on a scale from 1 (bad) to 5 (excellent).

[Evaluation Criteria]

1. Bad - The response is completely off-topic and difficult to understand.
2. Poor - The response is somewhat related to the question but contains grammatical or semantic errors, making it somewhat difficult to understand.
3. Fair - The response mostly aligns with the question, with few grammatical or semantic errors, and provides somewhat adequate information.
4. Good - The response aligns with the question, contains few grammatical or semantic errors, and provides adequate information.
5. Excellent - The response aligns with the question, contains almost no grammatical or semantic errors, provides adequate and appropriate information.

Output the evaluation score in the following format:

[Example Evaluation 1]

Question: Can you recommend an easy-to-write pen?

Answer: I recommend Mitsubishi Pencil Jetstream Standard.

Score: 5

[Example Evaluation 2]

Question: What is the highest mountain in the world?

Answer: I guess 3141010059.

Score: 1

[Evaluation Target]

Question: {Question}

Answer: {Answer}

Score:

Figure 5: Prompt for ChatGPT evaluation.

At the top of the screen, you will see the "Reference Text," and at the bottom of the screen, you will hear the audio of a conversation between two people. The conversation is in a QA format, with one person asking questions and the other responds. Please listen to the audio file with a headphone and evaluate it on a scale of 1 (poor) to 5 (good) based on the following two criteria:

(1) How natural is the system's response audio as a reading of the response text (the part after "A:" in the reference text)?

(2) Is the system's response speed sufficiently fast?

Please do not include the naturalness of the text content or the naturalness of the question audio in the score.

Figure 6: Instruction for speech evaluation.

Table 4: Ablation study. The suffix no-WL denotes weighted loss was not applied.

Method	Input modality	Output Modality	T-score \uparrow	S-score \uparrow	FR \downarrow	CER \downarrow
PSLM	SQ, TQ (Gold)	TA, SA	3.50 \pm 0.08	3.22 \pm 0.09	5.05	5.25
PSLM-2x	SQ, TQ (Gold)	TA, SA	3.50 \pm 0.08	3.20 \pm 0.09	4.29	6.39
PSLM-3x	SQ, TQ (Gold)	TA, SA	3.28 \pm 0.10	2.99 \pm 0.10	7.07	6.09
PSLM-no-pretrain	SQ, TQ (Gold)	TA, SA	2.22 \pm 0.07	2.12 \pm 0.07	18.18	10.13
PSLM-no-TQ	SQ	TA, SA	2.34 \pm 0.09	2.19 \pm 0.09	8.84	6.38
PSLM-no-SQ	TQ (Gold)	TA, SA	3.54 \pm 0.08	3.17 \pm 0.09	6.31	8.99
PSLM-2x-no-WL	SQ, TQ (Gold)	TA, SA	3.42 \pm 0.08	3.17 \pm 0.08	8.84	4.99
PSLM-3x-no-WL	SQ, TQ (Gold)	TA, SA	2.67 \pm 0.10	2.46 \pm 0.10	11.36	6.94