# Efficient Parallel Audio Generation using Group Masked Language Modeling

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*Abstract*—We present a fast and high-quality codec language model for parallel audio generation. While SoundStorm, a stateof-the-art parallel audio generation model, accelerates inference speed compared to autoregressive models, it still suffers from slow inference due to iterative sampling. To resolve this problem, we propose Group-Masked Language Modeling (G-MLM) and Group Iterative Parallel Decoding (G-IPD) for efficient parallel audio generation. Both the training and sampling schemes enable the model to synthesize high-quality audio with a small number of iterations by effectively modeling the group-wise conditional dependencies. In addition, our model employs a cross-attentionbased architecture to capture the speaker style of the prompt voice and improves computational efficiency. Experimental results demonstrate that our proposed model outperforms the baselines in prompt-based audio generation.

Index Terms-Parallel audio generation, neural audio codec

#### I. INTRODUCTION

ECENT development of neural audio codecs [1], [2] R has brought significant attention to large language models (LLM) as a promising avenue for audio generation. The transformer-based LLMs in Natural Language Processing (NLP) area have demonstrated their outstanding performance by capturing the long-term context and remarkable zero-shot capability through in-context learning [3], [4]. Inspired by this line of research, casting the audio generation in the continuous domain [5]–[7] to the discrete domain, by taking advantage of a powerful LLM, has unlocked rapid progress in versatile applications. Notably, [8] introduced an autoregressive transformer to model the discrete acoustic tokens, exploring its application in audio continuation tasks by using the audio prefix as a prompt. Furthermore, [9] and [10] successfully employed codec language models in zero-shot speech synthesis, using only a few seconds of an unseen prompt voice. Despite these advancements, the length of an acoustic token sequence generated from neural audio codecs is typically longer than that of natural language tokens due to its frame rate. This poses challenges for developing transformerbased discrete audio generation models that have quadratic runtime complexity.

To address this issue, prior research [11]–[15] proposed various methods to enhance computational efficiency. For

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Fig. 1. Overview of our proposed model

instance, [13] and [15] suggested novel codebook patterns to reduce iterations in autoregressive modeling, while [14] introduced a non-autoregressive diffusion model [16] for modeling the continuous acoustic token embedding. SoundStorm [11], the primary focus of this work, introduced a confidence-based parallel decoding technique for modeling the discrete acoustic token sequence. Leveraging the characteristics of residual vector quantization (RVQ)-based codebooks [2], the confidencebased parallel decoding technique significantly reduced the complexity of non-autoregressive models, generating acoustic tokens iteratively with fewer sampling passes. Although these approaches have somewhat improved inference speed, they still show slow generation due to their iterative nature.

Motivated by this problem, we propose a fast, highquality codec language model for parallel audio generation. As illustrated in Fig. 1, our approach focuses on semanticto-acoustic token generation given prompt acoustic tokens. We employ HiFi-Codec [17] for acoustic tokenization and Wav2Vec 2.0 [18] for semantic tokenization. HiFi-Codec provides Group-RVQ (G-RVQ)-based acoustic tokens, facilitating high-quality audio tokenization with more concise codebooks. Based on these G-RVQ acoustic tokens, we propose an efficient training algorithm, Group-Masked Language Modeling (G-MLM), which employs group-wise conditional dependency. Furthermore, we propose Group-Iterative Parallel Decoding (G-IPD), mirroring this training procedure, and verify that G-IPD enables our model to generate acoustic tokens with fewer iterations without compromising audio quality. Additionally, we propose a cross-attention-based prompting method, a computationally efficient structure for reflecting the speaker identity of the prompt voice.

# II. BACKGROUNDS

# A. Group Residual Vector Quantization (G-RVQ)

Residual Vector Quantization (RVQ), employed in Sound-Stream [2] and Encodec [1], encodes multiple streams of

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Fig. 2. Bi-group, bi-depth G-RVQ for acoustic tokenization

discrete tokens from audio, within the framework of VQ-VAE [19]. RVQ compresses each audio frame through cascaded quantizers, with each quantizer contributing residually to the encoding process, generating multi-level sequences of codewords. In this configuration, the initial level codebook retains the most fundamental audio information, and the number of quantization levels  $N_q$  controls the trade-off between computational cost and coding efficiency.

More recently, HiFi-Codec [17] introduced a Group Residual Vector Quantization (G-RVQ) scheme, demonstrating superior performance at lower bit rates. G-RVQ divides the latent features extracted from the encoder into G groups and applies RVQ to each group with  $N_q$  levels. For example, with a target bitrate of R = 2000 bps and 50 output frames per second, resulting in r = 2000/50 = 40 bits allocated to each frame, and for  $N_q = 2$  and G = 2, the total rate budget is evenly distributed among each Vector Quantization (VQ) layer, i.e.,  $r_i = r/(N_q * G) = \log_2 N$ . Consequently, the codebook size becomes  $N = 2^{r_i} = 2^{40/4} = 1024$ . As G-RVQ utilizes multiple initial levels of RVQ codebooks, it demonstrates a higher compression rate compared to RVQ.

## B. SoundStorm

SoundStorm is a non-autoregressive model designed for translating semantic tokens into acoustic tokens. Semantic tokens are derived from W2V-BERT [20] to encode coherent semantic information, while RVO-based acoustic tokens are extracted from the SoundStream [2] audio codec for encoding acoustic information. SoundStorm [11], comprising conformer blocks [21], is trained to predict masked acoustic tokens given the semantic tokens. The bidirectional conformer structure allows for acoustic token generation in an arbitrary order, ensuring prompt speaker and acoustic consistency. In order to improve the inference speed, SoundStorm applies the iterative sampling scheme of MaskGIT [22] for parallel audio generation. At each sampling iteration, the top-k predicted tokens with the highest confidence scores are kept fixed, while the rest are predicted again. The number of predicted tokens in each round is gradually increased, ensuring the conditional dependency between acoustic tokens and this process proceeds RVQ level-wise in a coarse-to-fine order. Although SoundStorm improves the inference speed compared to autoregressive models, it often compromises the speech quality when reducing the decoding iterations.

#### III. PROPOSED METHOD

# A. Tokenization

We perform k-means clustering for semantic tokenization over the 15th hidden representation of Wav2Vec 2.0 [18].



Fig. 3. Overall model architecture

Previous research [23], [24] showed that these discrete tokens effectively capture semantic information, even substituting phonetic sequences. For acoustic tokens, we leverage the bigroup bi-depth G-RVQ of HiFi-Codec as illustrated in Fig. 2. Let x represent a waveform, and  $z \in \mathbb{R}^D$  be a latent feature. The acoustic tokenization process is performed as follows:

$$\mathbf{z}^{1:D} = Enc(\mathbf{x})$$
  

$$\mathbf{q}^{0}_{0}, \mathbf{q}^{0}_{1}, \mathbf{q}^{1}_{0}, \mathbf{q}^{1}_{1}] = GRVQ(\mathbf{z})$$
  

$$\mathbf{q}_{c}, \mathbf{q}_{f} = [\mathbf{q}^{0}_{0}, \mathbf{q}^{0}_{1}], [\mathbf{q}^{1}_{0}, \mathbf{q}^{1}_{1}],$$
(1)

where  $\mathbf{q}_g^j \in \{1, 2, ..., C\}^T$  represents the acoustic token sequence for *j*-th quantizer level and *g*-th group. The maximum length and codebook size are denoted as *T* and *C*, respectively. We denote  $\mathbf{q}_c$  as the coarse-grained acoustic tokens and  $\mathbf{q}_f$  as the fine-grained acoustic tokens. Utilizing G-RVQ rather than RVQ can encode more abundant acoustic information, and its concise RVQ depth brings computational efficiency.

#### B. Model Architecture

As shown in Fig. 3 (a), our model builds upon the architecture of SoundStorm [11], employing a conformer [21] module and a masked language modeling approach [25]. For the input of the prediction network, we aggregate the embeddings of the semantic tokens and the corresponding frames of partially masked acoustic tokens. Then, our model predicts acoustic tokens given the prompt acoustic token embedding as a conditioning signal. The output embeddings from the prediction network are processed by separate heads for each RVQ level.

To capture the speaker information of the prompt voice, we employ a multi-head cross-attention module [26] in the prediction network, as shown in Fig. 3 (a). Let e denote the output of the prompt encoder and h be the output of the selfattention in the prediction network. The key, K and value, V are derived from e, and the query, Q is obtained from h. The multi-head cross-attention module operates as follows:

$$\mathbf{Q}_{i} = \mathbf{h} \mathbf{W}_{q}^{i}, \ \mathbf{K}_{i} = \mathbf{e} \mathbf{W}_{k}^{i}, \ \mathbf{V}_{i} = \mathbf{e} \mathbf{W}_{\mathbf{v}}^{i}$$
$$\mathbf{head}_{i} = Softmax(\frac{\mathbf{Q}_{i}\mathbf{K}_{i}}{\sqrt{d}})\mathbf{V}_{i}$$
$$\mathbf{c} = [\mathbf{head}_{1}, \dots, \mathbf{head}_{N_{k}}],$$
(2)



Fig. 4. Comparison of iterative inference process: (a) SoundStorm's IPD, and (b) proposed method's G-IPD technique. s denotes the iteration steps.

where  $\mathbf{W}_{a}^{i}$ ,  $\mathbf{W}_{k}^{i}$ , and  $\mathbf{W}_{v}^{i}$  denote the linear projections for the key, value, and query, respectively. In (2), c represents the context vector summarizing the prompt voice. By leveraging the cross-attention mechanism [26], there are distinct advantages compared to SoundStorm. Firstly, unlike SoundStorm, which requires semantic tokenization of the prompt sequence, our model seamlessly captures prompt information using only acoustic tokens. This simplifies the inference process by eliminating the necessity for semantic tokenization of the prompt sequence. Secondly, our cross-attention mechanism strategically caches the key and value, avoiding the need for repetitive computation of the prompt part throughout the iterative sampling process. As a result, the prompt part needs to be calculated only once during inference while maintaining the prompt speaker information.

# C. Training and Inference

To harness the full potential of G-RVQ acoustic tokens, we propose the Group-Masked Language Modeling (G-MLM) approach for training the model. In this training scenario, we first sample the prompt delimiter time step  $t \sim U[\epsilon, T-1]$ to separate prompt and target sequence, where  $\epsilon$  means a starting frame index. The tokens before t constitute the prompt acoustic tokens, while those after t form the target sequence for generation. Our core idea lies in the masking strategy outlined in Algorithm 1. When training the coarse-grained acoustic tokens  $\mathbf{q}_c = [\mathbf{q}_0^0, \mathbf{q}_1^0]$ , we apply the cosine-scheduling mask [11], [22] separately to  $q_0^0$  and  $q_1^0$  in temporal axis, while masking all of the fine-grained acoustic tokens. As the G-RVQ tokens are extracted from the same latent feature, we assume that  $\mathbf{q}_0^0$  and  $\mathbf{q}_1^0$  are highly entangled. Based on this assumption, our inter-group masking strategy reduces the modeling complexity by employing the group-wise conditional dependency. For training fine-grained acoustic tokens, we apply the cosine mask to the fine-grained acoustic tokens in the same manner. Our model exploits RVQ-depth-wise conditional dependency in this step by leaving coarse-grained acoustic tokens unmasked. Finally, our model is trained with the crossentropy loss using the ground-truth acoustic tokens as the target, and the loss is calculated only for the masked tokens.

For inference, we propose the Group Iterative Parallel Decoding (G-IPD) technique, mirroring the G-MLM training scheme. Fig. 4 illustrates a comparison between G-IPD and SoundStorm's IPD [11]. Both techniques initially predict coarse-grained acoustic tokens and subsequently fine-grained acoustic tokens. When predicting coarse-grained acoustic tokens, a confidence-based iterative sampling [11], [12], [22] scheme is employed. At each iteration, the predicted tokens with the highest confidence scores are fixed, while the rest are re-masked. The number of masked tokens for each round is gradually decreased, following cosine schedule [11]. The key difference from the SoundStorm [11]'s IPD is that our decoding scheme involves the acoustic token sequences from two distinct groups together in the search space for each iteration. Doubling the search space allows our model to exploit group-wise conditional dependency, resulting in fewer iterations without performance degradation. Furthermore, G-RVQ inherently encodes rich audio information even at lower bitrates than RVQ. This contributes to faster inference while keeping the audio quality. Once the coarse-grained acoustic tokens are generated, they are used as conditions for predicting fine-grained acoustic tokens in a single step.

Algorithm 1 Masking strategy for G-MLM

Input coarse-grained acoustic tokens  $\mathbf{q}_c$ , fine-grained acoustic tokens  $\mathbf{q}_{f}$ 

**Output** masked acoustic token  $q^M$ 

- 1:  $l \sim Bernoulli(0.5)$ ▷ Sample quantization level 2: **if** l = 0 **then** > Training the coarse-grained acoustic tokens
- 3:
- 4:
- $\begin{array}{l} \mathbf{q}_{c}^{M} = CosineMask(\mathbf{q}_{c}), \\ \mathbf{q}_{f}^{M} = EntireMask(\mathbf{q}_{f}) \\ \mathbf{e} \qquad \triangleright \text{ Training the fine-grained acoustic tokens} \end{array}$ 5: **else**
- $\mathbf{q}_{f}^{M} = CosineMask(\mathbf{q}_{f})$ 6:
- 7: end if 8:  $\mathbf{q}^M = Concat(\mathbf{q}_c^M, \mathbf{q}_f^M)$
- 9: return  $\mathbf{q}^M$

# **IV. EXPERIMENTS**

In this section, we evaluate the performance of our proposed model in prompt-based audio generation. To assess how well the model captures speaker consistency, the experiments were carried out in two scenarios: (1) the prompt speaker and the target speaker are the same, and (2) the prompt speaker and the target speaker are different. The second scenario is identical to the zero-shot voice conversion. Furthermore, we compare the runtime of our proposed model with the baseline. Our synthesized audio samples are publicly available at our demo page: https://jmhxxi.github.io/SoundGroup-demo/.

#### A. Experimental setup

1) Implementation details: Our proposed model was trained for 800k iterations on 4 NVIDIA RTX8000 GPUs. The batch size was 128, with a gradient accumulation of 2. In this study, we use the open-sourced neural audio codecs from the AcademiCodec<sup>1</sup> toolkit. Acoustic tokenization was performed using HiFi-Codec, producing 50 frames per second, resulting

<sup>&</sup>lt;sup>1</sup>AcademiCodec: https://github.com/yangdongchao/AcademiCodec.

in the target bitrate of  $50 \cdot 4 \cdot \log_2 1024 = 2000$  bps. Our proposed model was trained with all of the training datasets of Libri-TTS [27], and the HiFi-Codec was pretrained with the same datasets as in the original configuration. For evaluation, we used the Libri-TTS test-clean subset so that all speakers in the evaluation set were unseen during training. We randomly selected the evaluation set consisting of 720 sentences and 20 sentences per speaker. All the speech data were sampled with a sampling rate of 24 kHz. For semantic tokenization, we used the pre-trained Wav2Vec 2.0 XLSR [28], with a total of 512 clusters for k-means clustering, and they were temporarily aligned to corresponding acoustic tokens. We evaluated the runtime on the single NVIDIA RTX8000 GPU to compare inference speed.

2) Baselines: We employed the SoundStorm model with the SoundStream codec as a baseline architecture. To eliminate data dependencies, we trained the SoundStream codec using the same dataset as HiFi-Codec. Following the SoundStorm configuration, we utilized the 6000 bps SoundStream codec with  $N_q = 12$ . We compared the SoundStorm and the proposed model by varying iteration numbers. During decoding, we used (16, 1, 1, ..., 1) iterations of SoundStorm for N = 27 and greedy sampling for N = 12. Additionally, for different speaker prompt settings, we employed the variational inference-based (VITS) [29] voice conversion model as a baseline. We added ECAPA-TDNN [30] as a reference encoder to the VITS for speaker conditioning.

3) Evaluation metrics: We performed a Mean Opinion Score (MOS) test to assess synthesized speech quality, with 17 evaluators rating naturalness. To measure intelligibility, we computed the Character Error Rate (CER) using a pretrained Whisper [31] large model in official implementation. For speaker similarity, Similarity Mean Opinion Score (SMOS) and Speaker Embedding Cosine Similarity (SECS) were used. For SMOS evaluation, 17 listeners assessed how well the generated speech captured the speaker identity of the prompt speech. For SECS, we quantified the cosine distance between the speaker embeddings of the generated and prompt speech, using WavLM-TDNN [32] as a pretrained speaker verification model.

## B. Results and Analysis

1) Prompt-based audio generation: We present the results of prompt-based audio generation in Table I where  $N_c$  and N indicate the number of iterations for coarse acoustic tokens and the total number of iterations, respectively. Our proposed model demonstrates superior performance in all metrics compared to the SoundStorm baseline at the same number of iterations, N. Moreover, our proposed model exhibits significantly better performance when compared to the VITS-based model in different prompt speaker setting. This indicates the proposed model's excellence in speaker similarity, audio quality, and speech intelligibility. Notably, in the case of SoundStorm, remarkable performance degradation was observed when Nwas reduced to 12. In contrast, our proposed model maintained performance even with N = 6, surpassing the performance of SoundStorm (N=27). The performance drop of the proposed model (N=2) was induced by the absence of G-IPD

TABLE I Comparison of results for audio generation. MOS and SMOS are described with 95% confidence intervals.

Method	CER	SECS	MOS	SMOS
HEal Court Court of the				
with Same Prompt Speaker				
Ground Truth	0.71	0.737	$4.55 \pm 0.08$	$4.55 \pm 0.07$
SoundStorm $(N = 12)$	3.02	0.429	$3.24 \pm 0.07$	$3.99 \pm 0.07$
SoundStorm $(N = 27)$	2.87	0.437	$3.83{\pm}0.07$	$4.10{\pm}0.08$
Proposed $(N_c = 1, N = 2)$	2.90	0.412	3.06±0.07	3.63±0.08
Proposed $(N_c = 5, N = 6)$	2.69	0.475	$4.06 {\pm} 0.07$	$4.30 {\pm} 0.07$
Proposed ( $N_c = 11, N = 12$ )	2.57	0.476	$4.27 {\pm} 0.07$	$4.42 \pm 0.07$
Proposed ( $N_c = 26, N = 27$ )	2.36	0.487	$\textbf{4.49}{\pm 0.06}$	$\textbf{4.47}{\pm 0.06}$
With Different Prompt Speaker				
VITS + Ref. (conversion)	2.71	0.382	$3.39{\pm}0.08$	$3.82{\pm}0.07$
SoundStorm $(N = 12)$	3.23	0.381	$3.54 {\pm} 0.08$	$3.86 {\pm} 0.08$
SoundStorm $(N = 27)$	3.11	0.392	$3.86{\pm}0.08$	$4.24{\pm}0.07$
Proposed $(N_c = 1, N = 2)$	3.28	0.367	3.10±0.07	3.58±0.08
Proposed $(N_c = 5, N = 6)$	2.53	0.406	$4.11 {\pm} 0.07$	$4.22{\pm}0.07$
Proposed ( $N_c = 11, N = 12$ )	2.49	0.416	$4.38 {\pm} 0.07$	$4.51 \pm 0.06$
Proposed $(N_c = 26, N = 27)$	2.46	0.417	$4.41{\pm}0.07$	$4.54{\pm}0.05$



Fig. 5. Comparison of inference speed. The prompt semantic tokenization is only used in SoundStorm's sampling process, and presented SoundStorm's runtime is evaluated without prompt semantic tokenization

sampling, which failed to account for group-wise conditional dependency.

2) Inference speed: We compared the inference speed of our proposed model to that of SoundStorm. For a fair comparison, we fixed the total iteration number N = 27. As shown in Fig. 5, the proposed model is much faster than SoundStorm across all target and prompt lengths. Although the runtime of the self-attention module was dependent on the sequence length, our cross-attention-based architecture was less affected by the variations in prompt and target length. In particular, the runtime gap between proposed model and SoundStorm increase in long prompt setting, because proposed model avoids repetitive computation of prompt part throughout the inference process. As indicated in Table I, we expect that our proposed model can reduce N without a significant performance drop, resulting in much faster inference.

# V. CONCLUSION

We have proposed a fast and high-quality codec language model for parallel audio generation using Group-Masked Language Modeling. For future work, we plan to extend our proposed model to support the zero-shot multi-speaker textto-speech via a text-to-semantic translation model.

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