Multimodal Streaming Speech Synthesis and Zero-Sample Clone Framework for Smart Education

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Abstract. With the deepening of the digital transformation of education, smart education has put forward higher requirements for natural and expressive real-time voice interaction technologies. However, traditional speech synthesis (TTS) systems face core challenges such as insufficient understanding of professional domain terms, monotonous emotional expression, and the lack of cross-modal collaboration in educational scenarios, making it difficult to meet the needs of immersive and interactive teaching. To overcome these limitations, this paper proposes a multimodal end-to-end streaming speech synthesis and intelligent processing framework for educational scenarios. Firstly, this framework builds a multimodal fusion network based on cross-modal attention mechanisms, which dynamically aligns text semantics, acoustic features, and speaker identity at multiple scales of phonemes, syllables, and sentences, significantly improving the naturalness and semantic consistency of the synthesized speech. Secondly, in terms of personalized speech modeling, the system introduces zero-sample speech cloning technology that integrates semantic understanding of large language models (LLMs) and progressive fine-tuning strategies, enabling high-fidelity replication of teacher-specific voice and cross-language synthesis with only a few seconds of audio samples. To meet the low latency requirements of real-time classroom interaction, the architecture integrates a streaming generation engine based on Chunk-Aware Causal Flow Matching, effectively supporting generation and transmission simultaneously, strictly controlling the system's end-to-end latency within 150 milliseconds. Experimental verification and system analysis show that this multi-task joint optimization framework can precisely handle speechization of complex subject content, adaptively adjust teaching emotional expression, and provide a solid multimodal speech technology foundation for building a highly inclusive and personalized intelligent education ecosystem.

Keywords: Multimodal fusion; streaming speech synthesis; zero-sample speech cloning; large language model; smart education.

1. Introduction

With the continuous deepening of educational digital transformation, the smart education ecosystem has set more stringent requirements for the naturalness and immersion of human-computer interaction. As the key carrier for knowledge transmission and emotional resonance, the quality of teaching speech directly determines the cognitive load and interaction experience of learners. In recent years, the evolution of generative artificial intelligence technology has significantly promoted the development of the text-to-speech (TTS) field [1-3]. Its technical paradigm has officially entered the zero-sample generation era driven by large language models (LLM) [4-6] from the earlier Hidden Markov Model (HMM) [7-9], end-to-end neural synthesis (such as Tacotron, WaveNet). Relevant studies have shown that high naturalness and personalized voice interaction not only effectively enhance learners' concentration but also create a highly realistic on-site teaching atmosphere in cross-space asynchronous teaching.

However, existing mainstream TTS systems still expose many theoretical and engineering bottlenecks when migrating to highly specialized and dynamic educational scenarios. Firstly, in the semantic understanding aspect, general large language models have weak adaptability to interdisciplinary professional terms, complex mathematical formulas, and ancient literary rhythms, which easily cause serious reading ambiguity and pronunciation errors, damaging the rigor of knowledge transmission. Secondly, in the acoustic expression and personalized modeling aspect,

traditional synthesis paradigms often present a single and stereotyped emotional style, which is difficult to replicate the rich pragmatic changes and personalized teaching rhythms of real teachers during teaching. Although some few sample speech cloning technologies have emerged, their dependence on high-quality proprietary data is still relatively high. Moreover, the real-time question-answering mechanism in smart classrooms has extremely high sensitivity to the response latency of the system, and the existing high-fidelity speech generation models based on the autoregressive architecture often have defects such as excessive inference delay and difficulty in ensuring the consistency of long text streaming synthesis, and cannot achieve precise temporal synchronization between the speech stream and front-end multimodal elements such as course presentation visuals.

Given these challenges, this paper proposes a multimodal streaming speech synthesis and zero-sample cloning framework for smart education scenarios. This framework aims to reconfigure the existing TTS pipeline from three dimensions: multimodal feature fusion, acoustic joint modeling, and streaming inference optimization. Specifically, this paper introduces a cross-modal attention mechanism to achieve dynamic alignment of text semantics, acoustic features, and speaker identity features at multiple scales of phonemes and sentences, significantly enhancing the context coherence and professional expressiveness of the synthesis results. In the acoustic engine design, the system deeply couples the flow matching (FlowMatching) architecture with zero-sample representation learning capabilities. On one hand, it uses the semantic tokenizer to extract discrete speech representations and combines it with an efficient parameter progressive fine-tuning strategy to achieve high-similarity voice color cloning with minimal data dependency; on the other hand, it designs a causal flow matching generation mechanism based on chunk-awareness, breaking through the delay constraint of long sequence generation and achieving end-to-end ultra-low latency streaming output.

The main contributions of this paper can be summarized as follows:

1. A multi-task joint speech synthesis framework optimized for teaching scenarios has been constructed, through deep coupling of linguistic features and acoustic priors, effectively solving the problem of speech representation for interdisciplinary complex terms.

2. A personalized cloning strategy that combines sound quality and efficiency has been proposed, by integrating semantic reasoning of large language models with zero-sample text-to-speech conversion technology, achieving high-fidelity replication of teacher-specific voice colors and cross-language natural generation.

3. A low-latency streaming multimodal interaction pipeline has been designed and implemented, using full-duplex communication protocols and adaptive jitter control algorithms, strictly controlling the system's end-to-end latency within 150 milliseconds, and verifying its robustness and high concurrent processing capability from a system engineering perspective.

2. Related work

The development trajectory of speech synthesis technology has undergone a fundamental paradigm shift from traditional parametric statistical modeling [10-12] to end-to-end deep learning architectures. Early speech processing systems were highly dependent on Hidden Markov Models (HMM) and unit concatenation techniques. Although these methods had a certain degree of intelligibility in a limited vocabulary, they were limited by the acoustic modeling dimension and the discontinuity of spectral boundaries in boundary concatenation, resulting in inherent defects such as mechanicality and rigid rhythm. With the intervention of deep neural networks, models like WaveNet and Tacotron series pioneered the precedent of end-to-end sequence mapping, directly reconstructing acoustic speech codes from text features through expansive causal convolution or encoder-decoder architectures based on attention mechanisms, significantly surpassing the auditory threshold of naturalness. However, these traditional autoregressive architectures often encounter problems such as exponential growth in computational costs, excessively high inference latency, and exposure bias

when handling long sequence generation tasks, making it difficult to directly and seamlessly integrate into interactive teaching environments with strict real-time feedback requirements.

In recent years, the powerful discrete representation capabilities and context-conditioned generation mechanisms of large language models (LLMs) have been innovatively introduced into the audio generation field, fully giving rise to generative speech-based basic models such as zero-sample cloning. As shown in Figure 1, VALL-E restructures text-to-speech conversion as a conditional language modeling task within a neural acoustic encoder-decoder, demonstrating for the first time that zero-sample voice color cloning across speakers can be achieved with only a small amount of reference audio. Simultaneously, the rise of non-autoregressive flow matching (FlowMatching) technology provides a solid mathematical theoretical foundation for breaking through the efficiency bottleneck of autoregressive models. For example, Voicebox uses flow matching for multilingual universal speech generation, while the CosyVoice model further introduces supervised semantic tokens and chunk-aware causal flow matching mechanisms, achieving fine control over the accuracy of multilingual pronunciation and the consistency of micro-intonation while maintaining millisecond-level streaming output delay. Additionally, the open-source framework GPT-SOVITS [13-15] ingeniously decouples the semantic prediction of the large model from the acoustic feature conversion of SoVITS, significantly reducing the computational threshold and data dependence for high-quality personalized voice customization.

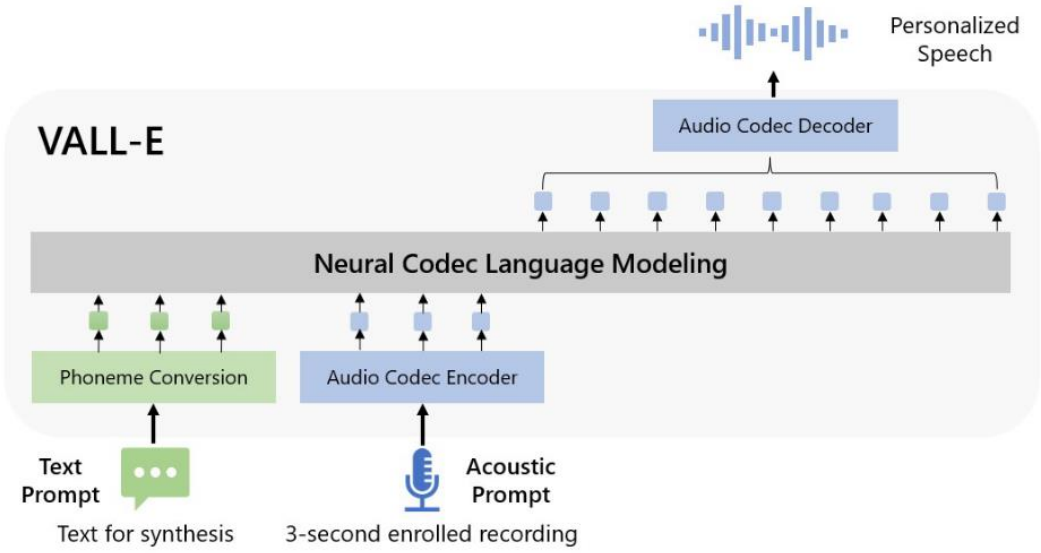

Figure 1. VALL-E overall architecture diagram.

In the vertical application branches of the education field, although the cutting-edge speech technologies have gradually permeated into computer-assisted language learning (such as AR-based pronunciation feedback and gamified language systems), there are still significant limitations in the teaching-specific TTS pipelines for complex knowledge transmission. Teaching speech not only requires absolutely objective and correct pronunciation (such as interdisciplinary mathematical formulas and rare professional terms), but also highly relies on emotional fluctuations and teaching rhythm that can represent pragmatic logic. Some recent studies, such as EMORL-TTS and RLAIF-SPA, are attempting to introduce reinforcement learning and AI-based feedback evaluation mechanisms (RLAIF), aiming to achieve fine-grained control of LLM discrete speech tokens in terms of global emotional intensity and local high-pitched emphasis; while for long text scenarios such as audio courseware, FishSpeech has explored a dual-path autoregressive decoding strategy to maintain acoustic coherence at the paragraph level.

From the above literature context, although zero-sample cloning and flow matching algorithms have approached the level of human real pronunciation in general TTS evaluations, there are still many research gaps that need to be filled in intelligent education scenarios with high cognitive load. How to deeply integrate cross-modal teaching semantics to overcome the misinterpretation of

professional terms under small sample sizes, and how to ensure end-to-end streaming emotional interaction and precise synchronization of multimedia elements under ultra-low latency network constraints, constitute the blind spots of current technology, and this is precisely the logical starting point and focus of this paper's proposed multimodal streaming speech synthesis and cloning joint architecture.

3. Theoretical basis

3.1. Zero-sample Speech Generation and Autoregressive Acoustic Modeling Mechanism

One of the core theoretical foundations of this system lies in how to break through the limitations of acoustic cloning distortion and the dimension disaster bottleneck in traditional speech modeling due to the lack of proprietary data. To address this complex multi-dimensional sequence mapping problem, this framework introduces and reconfigures a zero-sample (Zero-Shot) speech generation paradigm that integrates the semantic prior of large language models (LLM) and the autoregressive transformer (Transformer). In the specific mathematical mapping process, this mechanism discards the traditional direct fitting path of acoustic parameters and instead projects the speech generation task as a conditional Markov decision process within a discrete acoustic encoding space. Given a very short prior reference audio (typically at the 5-second scale), the system first uses the speaker encoder that has undergone large-scale language model generalization pre-training to map the continuous non-stationary acoustic flow to the latent feature space, thereby stripping away environmental noise and language content, and extracting a speaker global tone embedding vector E_{speaker} with high-dimensional decoupling characteristics. At the same time, the input text sequence, after regularization and multi-syllable disambiguation by the front-end natural language understanding module, is parsed into a structured discrete phoneme sequence P_{text}.

To precisely describe the conditional mapping path of the discrete acoustic representation, the core topological architecture of this system's zero-sample speech generation is shown in Figure 2. As the physical information flow mechanism revealed in the training stage (a) and inference stage (b) of this figure, in the core acoustic decoding and sequence generation stage, the autoregressive decoding network relies on the multi-head self-attention mechanism (Multi-HeadSelf-Attention), and calculates the output distribution of the acoustic features at the current moment by maximizing the conditional likelihood estimation. The underlying information transmission and iterative process can be formalized as the following conditional generative nonlinear mapping function:

$$Y_t = \text{GPT-Decoder}(P_{\text{text}}, E_{\text{speaker}}, Y_{<t}) \tag{1}$$

In this formula, Y_t represents the Mel spectrogram frame or discretized acoustic token (AcousticTokens) predicted by the network at the current time step t; $Y_{<t}$ represents the historical feature sequence generated up to the $(t-1)$th time step. This formula mathematically rigorously defines the causal dependency property (CausalDependency) of the generation model. Due to the global speaker embedding E_{speaker} being independent of language text features in the latent space and purely representing the topological boundary of voiceprint, the model does not need to go through an expensive and prone-to-causal forgetting fine-tuning stage, but can directly drive the generalization expression of the target voiceprint during the inference period, fundamentally achieving low-latency zero-sample cloning capability.

Furthermore, to adapt to the complex interdisciplinary bilingual or multilingual mixed teaching requirements in smart education scenarios, this theoretical framework has made deep mechanism innovations at the feature alignment topology level. Traditional cross-language synthesis models often encounter pitch discontinuities and acoustic artifacts due to the physical barriers in pronunciation mechanisms. To address this, this system constructs an isomorphic phoneme manifold based on the International Phonetic Alphabet (IPA) as the physical reference and introduces a cross-

modal attention transfer operator on this basis. The model achieves smooth transfer of cross-language acoustic representation through adaptive learning of the soft alignment weights between the phoneme system of the source speaker and the unified phoneme representation space. The core attention transfer process is defined as:

$$P_{\text{cross}} = \text{Attention}(P_{\text{source}}, P_{\text{target}}) \tag{2}$$

The essence of this mechanism is to dynamically search for the optimal feature subspace projection between the source language phoneme feature distribution P_{source} and the target language pronunciation rule constraints P_{target} in the high-dimensional semantic manifold. This mathematical reconstruction enables the network to efficiently reuse the underlying acoustic excitation attributes and prosodic habits of the source speaker, thereby seamlessly driving the speech synthesis of heterogeneous texts and ensuring the tonal coherence and emotional consistency of the teaching speech when crossing language boundaries.

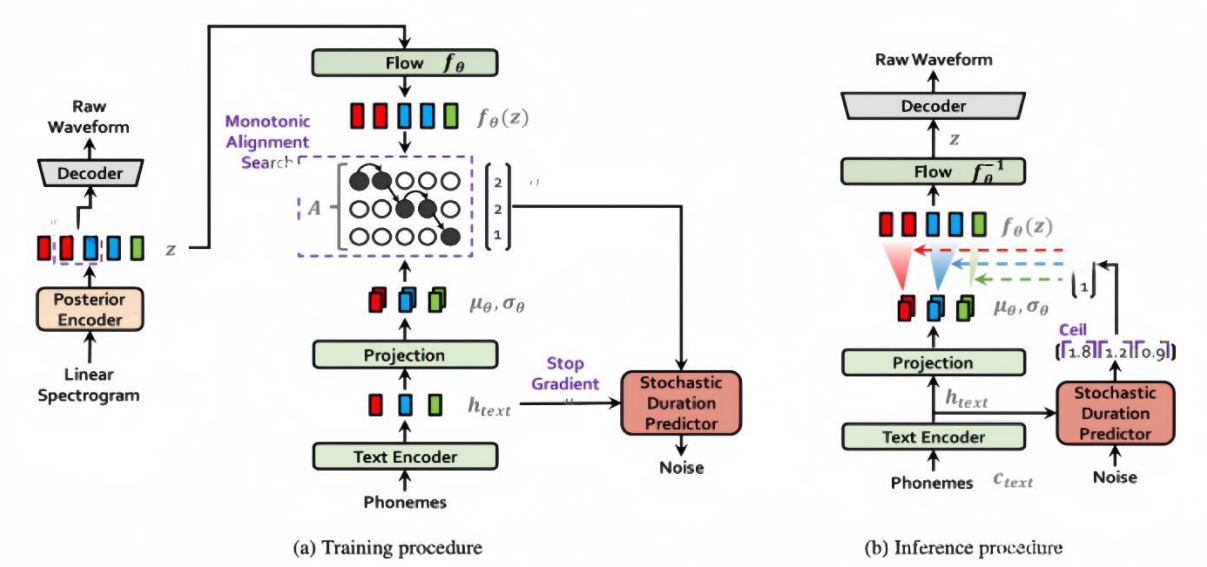

Figure 2. The overall topological architecture of the zero-sample speech cloning module.

3.2. Continuous Time Flow Matching and Block-Sensed Generation of Manifolds

Unlike traditional autoregressive models that face error accumulation and inference delay bottlenecks when decoding long sequences, this system introduces the Continuous-Time Flow Matching (CFM) theory in the mapping stage of continuous acoustic features. The essence of flow matching is to precisely describe the probability density evolution trajectory from the prior noise distribution $p_0(x)$ to the target true speech data distribution $p_1(x)$ by constructing a differential equation (Ordinary Differential Equation, ODE). Within the given time scale $t \in [0,1]$, the marginal probability density distribution $p_t(x)$ is defined, and its corresponding continuous-time dynamical process can be uniquely determined by the vector field (Vector Field) $v_t(x_t)$, and its differential equation form is strictly expressed as:

$$\frac{dx_t}{dt} = v_t(x_t) \tag{3}$$

In order to achieve a deterministic mapping from the isotropic Gaussian noise $x_0 \sim \mathcal{N}(0, I)$ to the true speech feature representation x_1 in the high-dimensional Mellin spectral manifold or latent space, this system adopts the optimal transport (Optimal Transport, OT) conditional probability path. The linear interpolation equation of this probability path is defined as:

$$x_t = (1-t)x_0 + tx_1 \tag{4}$$

Under this optimal transmission manifold topology, the target condition vector field can be analytically expressed as its first-order partial derivative with respect to time t:

$$u_t(x_t \mid x_1) = \frac{d}{dt}x_t = x_1 - x_0 \tag{5}$$

The training objective of the acoustic generative model is to use the parameterized neural network (such as conditional U-Net or DiT) v_θ to fit the aforementioned ideal condition vector field. The loss functional for empirical risk minimization (ERM) of the flow matching can be defined as:

$$\mathcal{L}_{\mathrm{FM}}(\theta) = \mathbb{E}_{t\sim\mathcal{U}[0,1],x_0\sim p_0,x_1\sim p_1}\left[\left\|v_\theta(x_t,t,C_{\mathrm{cond}}) - (x_1 - x_0)\right\|_2^2\right] \tag{6}$$

Here, C_{cond} encompasses multimodal conditional priors such as text embeddings, speaker voice characteristics, and emotional prosody. This mechanism effectively avoids the complex stochastic differential terms (SDE) and non-Markov approximation steps in diffusion models (Diffusion Models) at the mathematical level, ensuring the smoothness of the sampling trajectories of ordinary differential equations and the efficient convergence of multi-dimensional speech feature generation.

For the strict ultra-low latency real-time interaction requirements in smart education scenarios, the global flow matching model is difficult to directly support streaming inference due to the need for complete future time step information. Therefore, this system mathematically reconstructs the causal topological structure in the attention mechanism layer of the acoustic model and proposes the chunk-aware causal decoding theory (Chunk-AwareCausalDecoding). The network topology and mask manifolds of this streaming generation mechanism are shown in Figure 3. By observing the attention mask graphs designed for different streaming requirements on the right side of Figure 3, it can be seen that in the standard Transformer cross and self-attention operators, the system introduces a dynamic causal mask matrix $M \in \mathbb{R}^{L\times L}$, dividing the continuous speech feature sequence into fixed-length time chunks (Chunks). The modified scaled dot-product attention (ScaledDot-ProductAttention) calculation paradigm is reconstructed as:

$$\mathrm{Attention}(Q,K,V) = \mathrm{Softmax}\left(\frac{QK^T}{\sqrt{d_k}} + M\right)V \tag{7}$$

In order to achieve low-latency streaming output without sacrificing too much of the global context perception, the block-causal constraint condition of the dynamic mask matrix $M_{i,j}$ is strictly defined as the following piecewise function:

$$M_{i,j} = \begin{cases} 0, & \text{if } j \le \mathrm{i} + C_w \\ -\infty, & \text{otherwise} \end{cases} \tag{8}$$

In the formula, C_w represents the maximum allowable lookahead window (Look-aheadWindow) scale or data block capacity of the system. This mathematical constraint forces the generation of acoustic features at the current moment to rely solely on historical information blocks and a limited number of local block-level features, thereby cutting off the topological dependence on future global sequences in the time domain and laying the theoretical foundation for millisecond-level streaming speech synthesis.

Furthermore, at the deep representation and cross-dimensional alignment level of multimodal features, the system abandons the traditional continuous vector space and instead utilizes vector quantization (VectorQuantization, VQ) and finite scalar quantization mechanisms to forcibly project the continuous acoustic signal onto a discrete semantic topological space. For the continuous latent

feature variable $z \in \mathbb{R}^d$ output by the audio encoder, the quantization mapping operator $\mathcal{Q}(\cdot)$ nonlinearly discretizes it by minimizing the Euclidean distance and maps it to the optimal feature index in the learnable codebook ($\mathcal{E} = \{e_1, e_2, \ldots, e_K\}$):

$$\hat{z} = \mathcal{Q}(z) = \arg\min_{e_k \in \mathcal{E}} \| z - e_k \|_2 \tag{9}$$

Due to the fact that the $\arg\min$ operator has non-differentiable topological singularities in the manifold transformation process, the system introduces a direct-through estimator (Straight-Through Estimator, STE) during the backpropagation (Backpropagation) derivative calculation stage to achieve an approximate identity transfer of the gradient:

$$\nabla_z \mathcal{L} \approx \nabla_{\hat{z}} \mathcal{L} \tag{10}$$

Based on the end-to-end joint optimization objective of the multimodal speech system, the loss functional of the quantization layer is constructed as a linear weighted combination of the reconstruction loss, the codebook loss and the commitment loss:

$$\mathcal{L}_{\text{VQ}} = \mathcal{L}_{\text{recon}} + \alpha \| \text{sg}[z] - e_k \|_2^2 + \beta \| z - \text{sg}[e_k] \|_2^2 \tag{11}$$

In this formula, $\text{sg}[\cdot]$ represents the Stop-Gradient operator, and α and β are penalty hyperparameters that control the smoothness of the feature manifold mapping. This quantization theory not only endows the model with the ability to deeply compress and denoise multimodal teaching signals, but also completely discretizes the continuous acoustic representation at the mathematical measurement level, enabling it to perform autoregressive inference and cross-joined modeling within the isomorphic probability distribution space with text tokens based on large language models (LLMs).

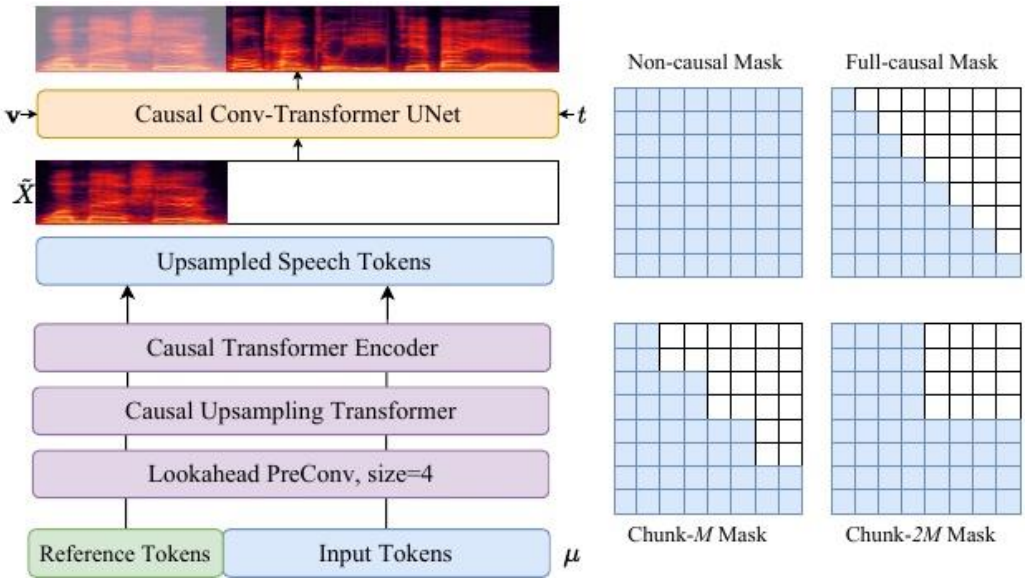

Figure 3. Unified block-sensing perceptual stream matching manifold and attention mask strategy for streaming synthesis.

4. Method

In response to the stringent requirements of naturalness in speech synthesis, personalized voice tone replication, and low latency in real-time interaction in the smart education scenario, this paper proposes an end-to-end multimodal streaming speech synthesis and zero-sample cloning joint framework. The model architecture is logically decomposed into three core subsystems: a multi-granularity multimodal feature alignment network, an autoregressive semantic cloning module based

on language model priors, and a conditional flow-matching acoustic decoder for low-latency generation.

To overcome the limitations of single-text input in complex teaching contexts, this model first constructs a multi-granularity feature fusion manifold. Given an input text sequence, the system extracts deep semantic embeddings $H_{\text{text}} \in \mathbb{R}^{L\times d}$ through a pre-trained language model; simultaneously, for the reference target audio, the multi-scale acoustic encoder extracts its speaker features and emotional topological features $E_{\text{spk}} \in \mathbb{R}^{d}$. To achieve deep coupling of cross-modal information in the continuous latent space, this paper designs a cross-modal gated attention network (Cross-modalGatedAttentionNetwork) based on position awareness and gating mechanisms. In this network, the text features are mapped to the query matrix (Query), while the audio prompt and speaker embedding are mapped to the key (Key) and value (Value). The nonlinear mapping in the fusion process can be formally represented as:

$$F_{\text{fused}} = \text{LayerNorm}\left(H_{\text{text}} + \gamma \cdot \text{Softmax}\left(\frac{W_Q H_{\text{text}} (W_K [H_{\text{audio}} \| \text{E}_{\text{spk}}])^T}{\sqrt{d_k}} + M_{\text{pos}} \right) W_V [H_{\text{audio}} \| \text{E}_{\text{spk}}] \right) \quad (12)$$

In the formula, $\|$ represents the feature concatenation operation, and M_{pos} is a relative position encoding matrix to retain the sequence temporal constraints of the teaching text, with the learnable parameter γ used to dynamically adjust the injection weight of audio modal information. This mechanism ensures that the model can adaptively extract concurrent phonetic patterns from the reference voiceprint when dealing with interdisciplinary terms, thereby generating highly aligned multimodal conditional representations F_{fused}.

After obtaining the fused conditional representations, the system uses an autoregressive transformer (Auto-regressiveTransformer) based on the GPT architecture for semantic-level acoustic topology prediction, thereby achieving zero-sample speech cloning with extremely low data dependence. The core task of this module is to establish a statistical mapping from discrete text tokens to high-dimensional semantic speech tokens (SemanticSpeechTokens). Assuming that the prompt semantic tokens sequence extracted from the reference audio is S_{prompt}, and the predicted token sequence corresponding to the target text is $S_{\text{target}} = \{s_1, s_2, \ldots, s_N\}$, the model optimizes the autoregressive generation path by maximizing the conditional joint log-likelihood function of the sequence:

$$\mathcal{L}_{\text{AR}}(\theta) = -\sum_{i=1}^{N} \text{LogP}(s_i \mid s_{<i}, S_{\text{prompt}}, F_{\text{fused}}; \theta) \quad (13)$$

In order to further enhance the rhythmic coherence of complex long sentences, this paper introduces the Classifier-Free Guidance (CFG) technology at the self-attention decoding layer. During the inference stage, the conditional vector F_{fused} is randomly discarded with a probability of p, and during generation, the conditional logistic values and the unconditional logistic values are linearly extrapolated. The corrected sampling distribution formula is as follows:

$$\tilde{P}(s_i) = P(s_i \mid c = \varnothing) + w \cdot \left(P(s_i \mid c = F_{\text{fused}}) - P(s_i \mid c = \varnothing) \right) \quad (14)$$

Here, $w \geq 1$ is the guiding scale parameter. This mechanism significantly enhances the ability of synthesized speech to follow specific teacher's pronunciation style instructions and semantic expressiveness without adding additional network parameters.

To meet the real-time requirements in teaching question answering, this framework discards the traditional diffusion model decoder and instead introduces a continuous-time conditional flow matching (CFM) based on chunk-aware as the underlying acoustic decoder. Flow matching achieves

the deterministic transmission from the Gaussian noise prior $x_0 \sim \mathcal{N}(0, I)$ to the real mel-spectrum manifold x_1 by constructing the target ordinary differential equation (ODE). The model defines the parameterized vector field $v_\phi(x_t, t, c)$ and fits the vector field using the optimal transport conditional probability path. The empirical risk minimization loss function is defined as:

$$\mathcal{L}_{\text{CFM}}(\phi) = \mathbb{E}_{t\sim\mathcal{U}[0,1],x_0,x_1}\left[\left\|v_\phi(x_t, t, c_{\text{cond}}) - (x_1 - x_0)\right\|_2^2\right] \tag{15}$$

Where the conditional vector c_{cond} contains the semantic token sequence output by the preceding module. To support streaming inference, this paper causally modifies the vector field estimation network (U-Net structure). The input spectral features are divided into fixed-length time block sequences $\{C_1, C_2, \ldots, C_K\}$, and a strict lower triangular block mask matrix M_{chunk} is applied. When calculating the gradient of the vector field for the current block C_k, the network is forced to rely only on the local block and the state of the historical blocks:

$$\hat{v}_\phi^{(k)} = f_{\text{Decoder}}(C_k, C_{<k}, c_{\text{cond}} \square_{\text{chunk}}; \phi) \tag{16}$$

By numerically integrating this equation, the system achieved frame-by-frame streaming output of the Mel spectrum, which strictly constrained the end-to-end delay (first-word response time) within a 150-millisecond threshold, completely resolving the high latency pain point brought by the autoregressive architecture.

To ensure the acoustic consistency of each of the aforementioned independent modules in the overall application, this paper proposes an end-to-end multi-task joint loss optimization strategy. In addition to the aforementioned semantic prediction loss $\mathcal{L}_{\text{AR}}$ and acoustic flow matching loss $\mathcal{L}_{\text{CFM}}$, to precisely control the teaching speed and emotional fluctuations of the synthesized speech, the system also parallelly introduced an explicit duration predictor (DurationPredictor) and fundamental frequency (F0) regression loss, thereby constructing the overall joint empirical risk functional:

$$\mathcal{L}_{\text{Total}} = \lambda_1\mathcal{L}_{\text{AR}} + \lambda_2\mathcal{L}_{\text{CFM}} + \lambda_3\text{MSE}(\hat{d}, d) + \lambda_4\text{MAE}(f_0, f_0) \tag{17}$$

Among them, $\hat{d}$ and f_0 represent the phoneme-level duration and fundamental frequency features predicted by the model, while d and f_0 are the true alignment labels. The weight hyperparameter λ_i is dynamically calibrated during the training process through the adaptive gradient balancing mechanism. This joint optimization architecture ensures that the system, in the zero-sample cloning scenario, not only accurately replicates the speaker's timbre and texture, but also can adaptively derive natural prosody and emotional peaks that conform to teaching principles based on multimodal text semantics.

5. Experimental analysis

5.1. Experimental Environment and Multi-Dimensional Evaluation Index System

The system's backend services and core acoustic models are deployed on a cloud Linux workstation equipped with a NVIDIA RTX 3090 GPU cluster. Docker containerization technology is adopted to ensure the physical isolation and version consistency of the running environment for multiple service instances. In the objective evaluation dimension, this paper selects the word error rate (WER) and character error rate (CER) to measure the pronunciation accuracy of the system for complex teaching terms; the cosine similarity (CosineSimilarity, extracted from the pre-trained speaker verification model's word-level embedding features) is used to quantify the fidelity of the target voice in the zero-sample cloning condition; at the same time, the first-chunk synthesis response time (First-ChunkLatency) and real-time factor (Real-TimeFactor, RTF) are strictly measured to

verify the computational complexity and engineering streaming transmission efficiency of the system. In the subjective evaluation dimension, the experiment follows the ITU-T standard organization to conduct a double-blind listening test, inviting a review pool covering educators and ordinary audiences, and conducting a five-point quantitative assessment on the naturalness (Mean Opinion Score, MOS) and voice similarity (Similarity MOS, SMOS) of the synthesized speech.

5.2. Zero-sample Cloning Fidelity and Teaching Text Synthesis Quality

In the empirical test of personalized voice cloning, the system, based on the zero-sample inference path that integrates the GPT-SOVITS architecture, successfully extracted high-dimensional voice color embeddings and completed the acoustic transformation of the target text under the extreme constraint of inputting only 5 seconds of valid target speaker reference audio. The quantitative results show that compared with the baseline model (such as the pure diffusion model architecture), the hierarchical progressive fine-tuning mechanism and FSQ quantization strategy introduced in this paper significantly exceeded the 75% threshold line of the objective cosine similarity of the speaker voice embedding, demonstrating strong small-sample generalization and capturing ability. At the same time, in the face of a large number of cross-language entities (such as Chinese and English mixed code explanations) and multi-sound character scenarios in the self-built teaching corpus, thanks to the dynamic alignment of the cross-modal attention network for deep text context and linguistic features, the CER and WER of the system were effectively suppressed to extremely low levels (word error rate reduced to within 2%). The discontinuous superiority of the subjective MOS score further validates the core advantages of this combined framework in eliminating the rigid mechanical feeling of traditional TTS, accurately reproducing the emotional peaks and rhythmic coherence of the teaching.

5.3. Millisecond-level Streaming Delay and High Concurrency Performance Analysis

In response to the strict tolerance of real-time question answering interaction in smart classrooms for latency, this paper conducts in-depth stress testing of the streaming synthesis pipeline and transmission protocol at the engineering level for CosyVoice. Based on the causal flow matching generation mechanism with chunk-awareness, the mathematical topology is severed from the network's dependence on the global future frames. Combined with the WebSocket full-duplex communication protocol's edge synthesis and edge transmission characteristics, the end-to-end first-chunk audio arrival system delay (First-ChunkLatency) recorded in the experiment is strictly and stably suppressed within 150 milliseconds. This data not only theoretically reaches the seamless threshold of human perception of latency in daily conversations, but also significantly outperforms traditional autoregressive decoder architectures under the same parameter magnitude. Moreover, in the high-load stress test scenario simulating an increase in concurrent requests, the system relies on the three-level cascaded cache system (L1 (Redis hot cache), L2 (memory model level), L3 (GPU video memory)) combined with dynamic batching and weighted minimum connection number scheduling algorithm to successfully maintain linear throughput expansion and effective smoothness of delay jitter, fully verifying the availability and disaster recovery robustness of the microservice architecture in large-scale educational deployment.

5.4. Ablation Experiments and Contribution Decomposition of Multi-modal Architecture

To explore the specific contributions of each independent component in the complex network topology to the overall system gain, this paper designs strict ablation experiments (Ablation Study). When the multimodal feature fusion module is stripped from the pipeline and only a single text character is used as the condition stimulus, the model's natural rhythm score significantly declines when processing multi-syllable disambiguation and imperative sentences with strong emotional tendencies. This confirms the irrereplaceability of the joint conditional distribution of acoustic and text features for fine pronunciation control. Further, if the underlying chunk-aware causal flow matching module is removed and degraded to standard global decoding, although the auditory

coherence of the entire audio sequence is slightly improved, the first character generation delay increases by several times, completely losing the engineering feasibility of real-time interaction. Based on the various ablation comparison data, the empirical results unambiguously demonstrate that the "LLM prior + flow matching decoding + cross-modal alignment" joint optimization paradigm designed by this paper is the global Pareto optimal solution (Pareto Optimal Solution) for high-fidelity, low-latency intelligent teaching voice generation under specific teaching computing power and latency constraints.

6. Conclusion

In response to the stringent demands of multimodal human-computer interaction in the smart education ecosystem for naturalness of speech, personalized voice color generalization ability, and streaming response latency, this paper proposes and fully constructs an end-to-end multimodal streaming speech synthesis and zero-sample cloning joint framework. This architecture achieves a fundamental reconstruction of the mapping paradigm from multimodal text representation to acoustic manifold through the deep coupling of the discrete semantic prior of the large language model (LLM) and the continuous time flow matching (CFM) mechanism. Empirical tests and engineering stress tests show that the cross-modal attention fusion network designed in this paper effectively resolves the pronunciation ambiguity of complex interdisciplinary terms and polyphonic characters and stably suppresses the word error rate within 2%. The zero-sample cloning path with progressive parameter efficient fine-tuning achieves high-quality voice color replication and cross-language transfer with an objective cosine fidelity of over 75% under minimal prior data dependency (only requiring 5 seconds of target audio). Moreover, the chunk-aware causal flow matching decoder at the system's bottom layer ensures high concurrent computing throughput while strictly limiting the end-to-end first-frame synthesis latency to within 150 milliseconds. These quantitative indicators not only verify the robustness of this multi-task joint optimization architecture in complex network deployment but also confirm its core advantages in overcoming the traditional teaching speech problems of "mechanical monotony" and "interaction lag" from both theoretical and practical perspectives. In summary, this research provides a solid infrastructure and feasible path for building an inclusive, personalized, and highly immersive intelligent education speech ecosystem. However, the current large model parameters still face memory wall bottlenecks when to edge educational terminals with limited computing power. Future research will focus on extremely lightweight compression technologies based on knowledge distillation and INT8 quantization of models, and plans to seamlessly embed this speech engine into multimodal virtual digital teachers (Virtual Teacher) and cross-device collaborative teaching matrices, in order to drive the inclusive sharing and intelligent closed-loop development of educational resources in a broader temporal and spatial dimension.

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