TED-TTS: Training-Free Intra-Utterance Emotion and Duration Control for Text-to-Speech Synthesis

Anonymous ACL submission

Abstract

While controllable Text-to-Speech (TTS) has achieved notable progress, most existing methods remain limited to inter-utterance-level control, making fine-grained intra-utterance expression challenging due to their reliance on non-public datasets or complex multi-stage training. In this paper, we propose TED-TTS, a training-free controllable framework for pretrained zero-shot TTS to enable intra-utterance emotion and duration expression. Specifically, we propose a segment-aware emotion conditioning strategy that combines causal masking with monotonic stream alignment filtering to isolate emotion conditioning and schedule mask transitions, enabling smooth intra-utterance emotion shifts while preserving global semantic coherence. Based on this, we further propose a segment-aware duration steering strategy to combine local duration embedding steering with global EOS logit modulation, allowing local duration adjustment while ensuring globally consistent termination. To eliminate the need for segment-level manual prompt engineering, we construct a 30,000-sample multi-emotion and duration-annotated text dataset to enable LLM-based automatic prompt construction. Extensive experiments demonstrate that our training-free method not only achieves state-of-the-art intra-utterance consistency in multi-emotion and duration control, but also maintains baseline-level speech quality of the underlying TTS model. Audio samples are available at https://aclanonymous111.github.io/TED-TTS-DemoPage/.

1 Introduction

Humans naturally regulate emotional expression and speaking pace during speech in a dynamic and flexible manner, reflecting changes in semantics, emphasis, and discourse intent. How to replicate such intra-utterance expressiveness remains a central challenge in building human-like Text-to-Speech (TTS) synthesis systems.

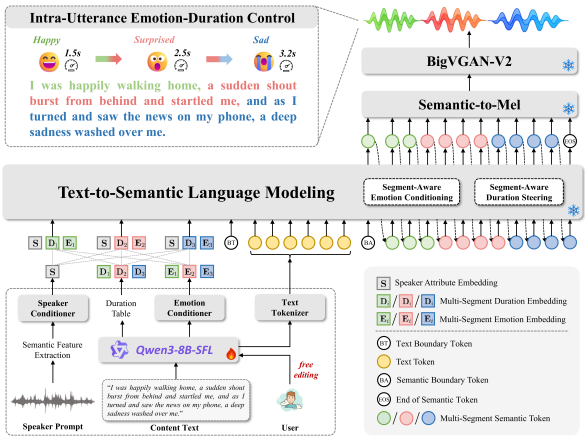

Figure 1: Overview of our training-free framework for intra-utterance emotion and duration control, where the green, red, and blue regions denote three segments with different emotion and duration settings within the same utterance.

Recent advances in controllable TTS have enabled zero-shot synthesis conditioned on attributes such as speaker identity, emotion, and speaking rate (Du et al., 2024b; Wang et al., 2025c,b; Chen et al., 2025; Gao et al., 2025; Yang et al., 2025; Zhou et al., 2025). Despite these advances, controllability in most existing methods remains confined to the utterance level, where a single emotional or prosodic condition is uniformly applied to an entire utterance, deviating from the dynamic expression naturally observed in human speech. To address this limitation, some methods (Luo et al., 2021; Tan et al., 2024) predict phoneme- or frame-level affective attributes directly from text, while others (Kanda et al., 2024; Wu et al., 2024) rely on emotional reference speech to guide localized expressive patterns, such as brief laughter or crying. Most recently, WeSCon (Wang et al., 2025a) proposes a self-training framework with transition smoothing and emotional-bias mechanisms, enabling the TTS model to render multiple emotions within an utterance through distillation. While these meaningful

progress, they typically rely on large-scale time-aligned annotated speech datasets or involve multi-stage training pipelines, which substantially limit their cross-model transferability and real-world deployment.

These challenges naturally raise an important question: ***Is it possible to achieve stable segment-level emotion transitions and duration control without retraining the model?*** In this paper, as shown in Fig. 1, we revisit controllable TTS from an inference-time perspective and propose the first **T**raining-free Intra-Utterance **E**motion and **D**uration control framework (TED-TTS). Rather than introducing additional predictors or retraining the acoustic model, our approach focuses on restructuring how conditioning information is accessed and updated during autoregressive decoding. Specifically, for multi-emotion control, we propose a segment-aware emotion conditioning strategy that combines causal masking with monotonic stream alignment filtering algorithm, which jointly isolates segment-specific emotion conditioning and performs online text-semantic alignment to schedule mask transitions, enabling smooth intra-utterance emotion shifts while preserving global semantic coherence. To enable multi-duration control, we further propose a segment-aware duration steering strategy to incorporate local duration embedding steering with global EOS logit modulation, allowing segment-level pacing adjustment while ensuring globally consistent sequence termination. Besides, we construct a multi-emotion and duration-annotated text dataset with 30,000 samples and fine-tune Qwen3-8B to enable LLM-based automatic prompt construction, thereby eliminating the need for segment-level manual segmentation and prompt engineering. Extensive experiments demonstrate that our method achieves state-of-the-art performance in stable intra-utterance multi-emotion transitions and duration control, while preserving the strong zero-shot synthesis capability of the underlying TTS model without any additional training. Our contributions are summarized as follows:

- We propose a training-free controllable framework for intra-utterance-level TTS, and eliminate manual prompt engineering by constructing a 30,000-sample multi-emotion and duration-annotated text dataset for LLM-based automatic prompt construction.
- We propose a segment-aware emotion conditioning strategy to jointly isolate segment-specific emotion conditioning and perform online text-semantic alignment, enabling stable multi-emotion transitions within a single utterance.
- We propose a segment-aware duration steering strategy that achieves local segment duration control while preserving global consistent sequence termination.
- Extensive experiments demonstrate that our training-free method not only achieves state-of-the-art intra-utterance consistency for multi-emotion and duration control, but also maintains the baseline-level speech quality of the underlying TTS model.

2 Related Work

2.1 Emotionally Controllable TTS

Emotion-controllable TTS methods can be broadly categorized by the modality of emotion prompts. **Speech-prompt-based methods** condition synthesis on reference emotional utterances and can transfer fine-grained affective cues such as intensity and prosody (Eskimez et al., 2024; Du et al., 2024a; Wang et al., 2025c,b; Chen et al., 2025), but their reliance on reference speech limits practical flexibility. In contrast, **Text-prompt-based methods** offer more flexible control, where early approaches rely on discrete emotion labels (Guo et al., 2023a; Kang et al., 2023; Diatlova and Shutov, 2023; Tang et al., 2024; Gao et al., 2025), while recent methods adopt natural language emotion descriptions for richer and more continuous conditioning (Guo et al., 2023b; Liu et al., 2023; Yang et al., 2024; Du et al., 2024b; Yang et al., 2025; Zhou et al., 2025). However, these methods typically operate at the utterance level, assigning a single global emotion to an entire utterance and thus failing to capture intra-utterance emotional dynamics. To address this limitation, several **Intra-utterance control methods** predict fine-grained affective attributes directly from text (Im et al., 2022; Luo et al., 2021; Tan et al., 2024), or incorporate emotional reference speech to enable localized expressions such as laughter or crying (Kanda et al., 2024; Wu et al., 2024). More recently, WeSCon (Wang et al., 2025a) introduces a self-training framework to support multi-emotion rendering within a single utterance. Despite these advances, existing methods often rely on large-scale non-public emotional

datasets or multi-stage training pipelines that hinder their scalability and cross-model transferability, leaving training-free intra-utterance emotion control as an open and practically valuable challenge.

2.2 Duration Controllable TTS

Current exploration on duration control has advanced along both non-autoregressive and autoregressive approaches. **Non-autoregressive methods** achieve duration control via explicit duration predictors based on diffusion-transformers (Lee et al., 2025), flows (Kim et al., 2023), or language models (Du et al., 2025), but these predictors are trained separately and often struggle with temporal accuracy under prosodic variability. In contrast, **autoregressive methods** lack inherent duration control and typically rely on auxiliary cues, such as natural-language timing prompts (Zhou et al., 2024) or specialized attributes and labels (Li et al., 2025; Sahipjohn et al., 2024; Wang et al., 2025b). More recently, IndexTTS2 (Zhou et al., 2025) improves controllability by conditioning semantic token generation on duration positional embeddings, enabling more stable alignment between desired and produced token lengths than earlier autoregressive methods. However, existing approaches still struggle to decouple local pacing from global generation, failing to provide a unified framework that ensures stable intra-utterance duration control without compromising overall alignment.

2.3 Inference-Time Controllable TTS

Several approaches have explored inference-time controllable TTS, enabling flexible manipulation of speech attributes. EmoKnob (Chen et al., 2024) injects scaled emotion difference vectors into speaker embeddings for emotion control, while PRESENT (Lam et al., 2025) performs rule-based prosody shaping by adjusting pitch, duration, and energy predictions from text prompts. SPTTS (Suni et al., 2025) further operates in the latent embedding space, manipulating prosody and style directions derived via linear regression and vector arithmetic. More recently, EmoSteer-TTS (Xie et al., 2025) directly steers token-level activations in pretrained diffusion-based TTS models, enabling training-free emotion control with improved interpretability over global embedding methods. However, these methods predominantly focus on implicit latent manipulation or isolated feature editing, and lack a unified framework for jointly controlling segment-level emotion and pacing transitions.

3 Method

In this section, we introduce a training-free controllable framework for intra-utterance emotion and duration transitions, with details provided in the following subsections.

3.1 Automatic Prompt Construction

Existing intra-utterance controllable TTS systems require manual text segmentation and segment-level emotion and duration specification, which is labor-intensive in real-world scenarios. To eliminate manual prompt engineering, we fine-tune the Qwen3-8B LLM to automatically transform raw user text into structured multi-segment prompts. As a prerequisite, we construct a dedicated **M**ulti-**E**motion and **D**uration-annotated text dataset (MED-TTS) with 30,000 samples, which is used to supervise emotion-aware text segmentation, natural language emotion description generation, and segment-level speech duration estimation. As illustrated below, MED-TTS is synthesized using LLM through a structured pipeline consisting of generation, annotation, and verification.

Step 1: Content text generation. GPT-4o is prompted to generate emotion-rich English and Chinese texts with continuous intra-utterance emotional transitions spanning multiple phases from seven core emotions (*happy, sad, angry, surprised, fearful, disgusted,* and *neutral*), covering descriptive, dialog-style, and observational content in three text categories.

Step 2: Multi-segment prompt annotation. To enable precise segment-level control, DeepSeek-Chat is prompted to decompose each text into emotion-specific segments and assigns each segment a concise natural language emotion description and a realistic duration estimate, yielding structured emotion-duration sequences compatible with controllable TTS inputs.

Step 3: Post-processing and manual verification. Automatic checks are finally applied to filter samples with formatting errors, missing fields, or invalid segment boundaries, followed by systematic manual verification of outputs from both Step 1 and Step 2. Based on this dataset, we perform supervised fine-tuning with LoRA on the Qwen3-8B large language model, enabling automatic construction of segment-level TTS prompts without manual prompt engineering. Detailed prompting strategies, step-wise checklists, dataset statistics, and fine-tuning details are provided in the Appendix A.

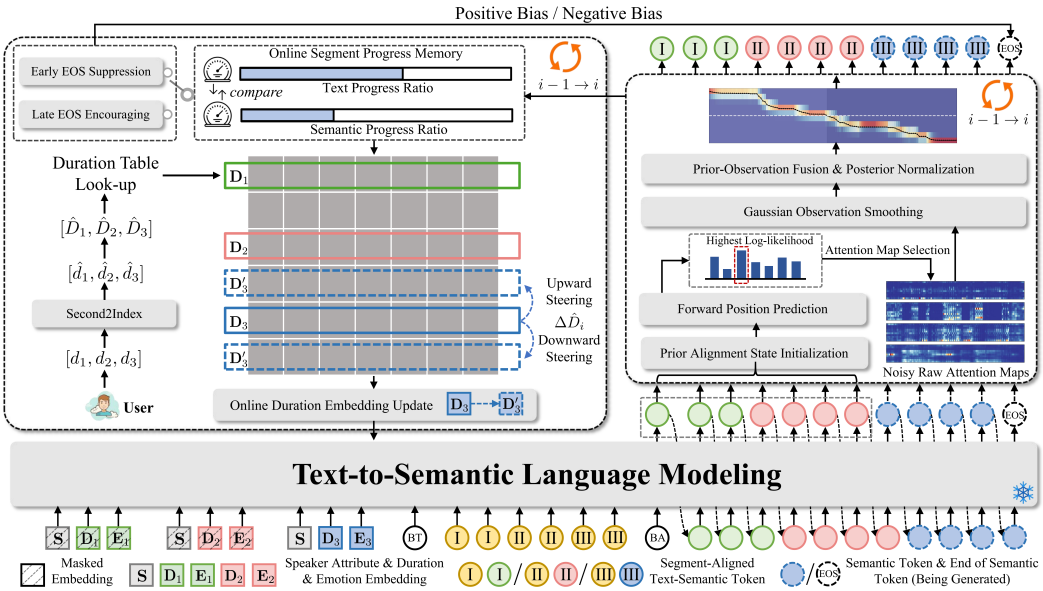

Figure 2: Overview of our training-free framework for fine-grained intra-utterance emotion and duration control, illustrating the transition from the second (red) segment to the third (blue) segment via segment-aware duration steering (left) and segment-aware emotion conditioning (right) strategy.

3.2 Segment-Aware Emotion Conditioning

Our TTS architecture follows the same configuration as the IndexTTS2 (Zhou et al., 2025) baseline, and we focus our design on its text-to-semantic (T2S) module to enable training-free intra-utterance emotion control. Specifically, T2S is formulated as an autoregressive semantic token prediction task conditioned on text and a set of control embeddings. Given an input text, represented by the yellow tokens in Fig. 2, we decompose it into M user-defined segments $\mathbf{X} = \{\mathrm{X}_1, \mathrm{X}_2, \ldots, \mathrm{X}_M\}$, and each segment X_m is assigned a condition embedding $\mathbf{C}_m = \{\mathbf{I}, \mathbf{E}_m\}$, where $\mathbf{I}$ denotes a fixed speaker identity embedding shared across the segment, and $\mathbf{E}_m$ represents segment-specific emotion conditions. However, in autoregressive T2S formulations, semantic tokens are generated as a continuous stream without explicit segment boundaries, making it non-trivial to apply segment-level conditions to their corresponding text segments while preserving semantic continuity. To address this challenge, we propose a 2D causal attention mask combined with a monotonic stream alignment algorithm to enable smooth intra-utterance emotion transitions.

2D Causal Attention Mask. To resolve the misalignment between continuous generation and segment-level conditions, we design a 2D causal attention mask that disentangles condition visibility from semantic context. The mask preserves standard causal attention among text and semantic tokens across segment boundaries, ensuring globally coherent semantic generation while strictly restricting access to condition embeddings to be segment-local. Specifically, for any token that belongs to the m-th segment (either a text token in X_m or a generated semantic token that currently aligns to X_m), attention is allowed to attend only to its corresponding condition embedding $\mathbf{C}_m$, while all other condition embeddings $\{\mathbf{C}_j \mid j \neq m\}$ are masked out. Meanwhile, each condition embedding $\mathbf{C}_m$ is prevented from attending to other condition embeddings, avoiding cross-condition information leakage. After that, as shown in the bottom of Fig. 2, emotional style is governed exclusively by the locally active condition, whereas semantic content remains globally visible through standard causal context.

However, applying 2D causal attention masks requires real-time knowledge of the alignment between generated semantic tokens and source text tokens. While transformer attention can provide alignment cues, raw attention maps are often noisy, head-dependent, and non-monotonic, making them unreliable for driving mask transitions. To address this, we propose an online **M**onotonic **S**tream **A**lignment (MSA) algorithm that performs Bayesian-style alignment tracking using attention as observation.

Monotonic Stream Alignment (MSA). As shown in Fig. 3, we use $\mathbf{A}_i \in \mathbb{R}^{L \times H \times T}$ denote

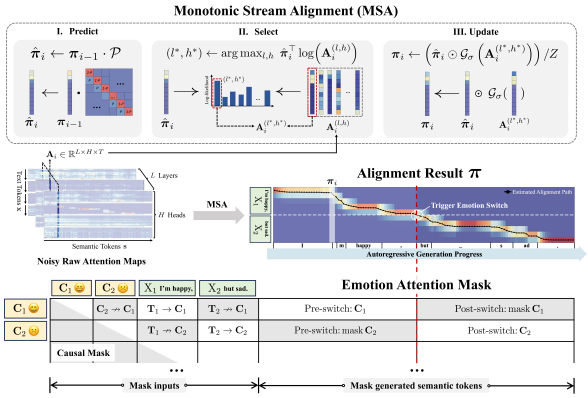

Figure 3: Detailed illustration of Monotonic Stream Alignment (MSA) in segment-aware emotion conditioning, where from top to bottom are MSA algorithm, MSA alignment result, and the visualization of 2D causal attention mask, respectively.

the raw attention maps from the current semantic token $\mathbf{s}_i$ to the T text tokens across L layers and H heads, where $\mathbf{A}_i^{(l,h)}$ is the attention vector of head (l, h). During online autoregressive decoding, MSA maintains a belief distribution over text positions to track the alignment of $\mathbf{s}_i$, represented by a prior distribution $\hat{\boldsymbol{\pi}}_i$ and a posterior distribution $\boldsymbol{\pi}_i$, both defined over the T text tokens. At each decoding step i, MSA first performs the *Predict* step by propagating the posterior $\boldsymbol{\pi}_{i-1}$ from the previous step forward along the text sequence using a monotonic transition operator $\mathcal{P}$. This propagation yields a prior distribution $\hat{\boldsymbol{\pi}}_i$ that encodes strong temporal monotonicity, encouraging gradual forward movement while suppressing backward alignment. After obtaining the monotonic prior $\hat{\boldsymbol{\pi}}_i$, MSA enters the *Select* step to select the most reliable attention head by measuring how well each head's attention distribution agrees with the predicted alignment:

$$(l^*, h^*) = \arg\max_{l,h} \hat{\boldsymbol{\pi}}_i^\top \log \mathbf{A}_i^{(l,h)}, \qquad (1)$$

where $\mathbf{A}_i^{(l,h)}$ denotes the attention vector of head (l, h). The resulting head (l^*, h^*) provides the most reliable attention observation used in the subsequent update. In the final *Update* step, MSA combines the selected attention observation $\mathbf{A}_i^{(l^*,h^*)}$ with the monotonic prior $\hat{\boldsymbol{\pi}}_i$ to compute the posterior alignment belief as:

$$\boldsymbol{\pi}_i = \frac{\hat{\boldsymbol{\pi}}_i \odot \mathcal{G}_\sigma\left(\mathbf{A}_i^{(l^*,h^*)}\right)}{Z}, \qquad (2)$$

where $\odot$ denotes element-wise multiplication, $\mathcal{G}_\sigma(\cdot)$ is a Gaussian smoothing operator, and Z is a normalization factor. This update incorporates real-time attention evidence while enforcing monotonicity, resulting in a stable alignment trajectory $\boldsymbol{\pi}_i$. Benefiting from this alignment trajectory, segment-level causal mask switching is triggered by tracking the expected aligned text position, enabling subsequent semantic tokens to attend to the new segment condition. More detailed mathematical derivations are provided in Appendix B.

3.3 Segment-Aware Duration Steering

Beyond segment-level emotional expressiveness, we further extend our emotion control framework to enable multi-segment duration control in a fully training-free autoregressive setting.

Local Duration Embedding Steering. Inspired by IndexTTS2 (Zhou et al., 2025), we condition duration control on a dedicated duration embedding indexed by the semantic token length, and tie its embedding table $\mathbf{W}_{dur}$ with the semantic positional embedding table $\mathbf{W}_{sem}$ to align autoregressive positional progression with target duration. As shown in Fig.2, given an utterance with M segments and desired durations $\mathbf{d} = \{d_1, d_2, \ldots, d_M\}$, each segment duration is converted into the corresponding number of semantic tokens according to the codec token rate (Wang et al., 2025c), yielding $\hat{\mathbf{d}} = \{\hat{d}_1, \hat{d}_2, \ldots, \hat{d}_M\}$. We accumulate segment-level targets into cumulative token lengths $\hat{D}_i = \sum_{k=1}^{i} \hat{d}_k$ and retrieve segment-wise initial duration embeddings as $\mathbf{D}_i = \mathbf{W}_{dur}[\hat{D}_i]$, which are concatenated into the segment-level conditioning inputs $\mathbf{C}_m$ to guide subsequent generation.

During autoregressive decoding, the actual semantic token generation speed may deviate from the user-specified target due to alignment uncertainty and model stochasticity. To correct such deviations online, we introduce a local duration embedding steering mechanism that dynamically updates the duration embedding via adaptive duration table lookup. At each decoding step i, we leverage MSA (Section 3.2) to estimate the current aligned text position and compute two normalized progress indicators within the active segment: text progress r_{text} and semantic progress r_{sem}. Their discrepancy is defined as $\Delta r = r_{text} - r_{sem}$, where a positive value indicates lagging semantic generation, which is then used to adjust the effective semantic token length via a proportional controller:

$$\Delta\hat{D}_i = \mathrm{clip}(\lfloor k \cdot \Delta r \rceil,\ -\Delta_{\max},\ \Delta_{\max}), \qquad (3)$$

where k controls the correction strength, $\lfloor \cdot \rceil$ denotes rounding to the nearest integer, and $\Delta_{\max}$ bounds the maximum adjustment. The effective segment-wise target is updated as $\hat{D}_i + \Delta\hat{D}_i \rightarrow \hat{D}'_i$, and the duration table $\mathbf{W}_{dur}$ is re-queried only for the active segment to obtain the updated duration embedding $\mathbf{D}'_i$, while duration embeddings of other segments remain unchanged. For stability, updates are applied at a low temporal frequency, allowing multiple consecutive semantic tokens to share the same duration embedding.

Global EOS Steering. In autoregressive decoding, the End-Of-Semantic (EOS) token determines sequence termination and overall duration. While local duration embedding steering regulates local generation pace, it does not explicitly control when decoding ends. To address this, we introduce a global EOS steering strategy that modulates sequence termination by applying adaptive biases to the EOS logit. Specifically, EOS generation is suppressed in all non-final segments to prevent premature termination, and in the final segment, the EOS logit is progressively adjusted based on the remaining semantic budget, discouraging early termination while smoothly encouraging EOS emission as the target budget is approached. Detailed parameter settings are provided in Appendix C.

4 Experiments

Datasets and Comparison Models. We use the MED-TTS dataset for content text, text-based emotion prompts, and duration annotations, which contains 15,000 English and 15,000 Chinese pair samples. For each language, 500 samples are randomly held out for evaluation, while the remaining samples are used for Qwen3-8B fine-tuning. For identity and emotion speech prompts, we adopt the Emotional Speech Dataset (ESD) (Zhou et al., 2022), where a same-language speaker is fixed per test utterance to ensure timbre consistency, and the speaker's emotional speech is used as segment-level emotion references.

We compare our method with representative controllable TTS methods spanning both non-autoregressive and autoregressive frameworks. The non-autoregressive models include MaskGCT (Wang et al., 2025c) and F5-TTS (Chen et al., 2025). The autoregressive models include CosyVoice2 (Du et al., 2024b), Spark-TTS (Wang et al., 2025b) and IndexTTS2 (Zhou et al., 2025).

Evaluation Metrics. We adopt both objective and subjective metrics to comprehensively evaluate system performance. Intelligibility is measured by WER for English using Whisper-Large (Radford et al., 2023) and CER for Chinese using Paraformer (Gao et al., 2022). Speaker similarity (S-SIM) is computed as the cosine similarity between WavLM-Large speaker embeddings (Chen et al., 2022). Transition smoothness is assessed using DNSMOS-Pro (DNSM) (Cumlin et al., 2024) over sliding speech segments, while perceptual quality is evaluated with NISQA (Mittag et al., 2021) and OVRL (Reddy et al., 2022). Emotional accuracy is evaluated based on the emotion prompt type, using emotion2vec-Large embeddings (Ma et al., 2024) for speech prompts and a fine-tuned emotion2vec classifier for text prompts. Subjective evaluation is conducted using four MOS criteria: SMOS for speaker similarity, NMOS for the naturalness of emotion transitions, EMOS for emotion alignment, and SPMOS for speaking rate accuracy. All scores are collected on a 5-point scale and reported with mean values and 95% confidence intervals.

5 Results and Evaluation

5.1 Comparison with Reference Models

Objective Evaluation. Since comparative methods lack intra-utterance controllability, all segments are synthesized independently and concatenated for evaluation. Under this setting, we conduct objective evaluations for both emotion and duration control. For emotion control, results are reported under two prompting settings: speech emotion prompts and text emotion prompts. For duration control, emotion is fixed to neutral, and segment-level speech synthesis is evaluated under five duration scaling factors (0.75, 0.875, 1.0, 1.125, and 1.25). As shown in Tab. 1, our method achieves the best overall performance on most objective metrics across both languages and prompting settings, with consistent gains on DNSM and SSIM indicating smoother emotion transitions and improved speaker consistency. Although WER/CER and emotion recognition scores are not always optimal, they remain comparable to the IndexTTS2 baseline, which is expected for a training-free framework. For duration control, as shown in Tab. 2, our method attains the best DNSM, NISQA, and OVRL scores in both languages, reflecting more stable temporal pacing and improved perceptual quality. While some methods achieve higher SSIM, this advantage largely stems from segment-independent synthesis under

	Model	WER/CER↓	DNSM↑	SSIM↑	NISQA↑	OVRL↑	Emo2v↑	SMOS↑	NMOS↑	EMOS↑
Speech Emotion Prompt										
English	MaskGCT	3.520	3.829	0.347	4.475	3.275	0.854	$2.96_{\pm 0.34}$	$2.77_{\pm 0.28}$	$3.64_{\pm 0.24}$
	F5TTS	2.632	3.674	0.353	4.427	3.330	0.832	$3.33_{\pm 0.36}$	$3.40_{\pm 0.32}$	$3.56_{\pm 0.28}$
	SparkTTS	2.433	3.456	0.358	4.494	**3.404**	0.849	$3.49_{\pm 0.29}$	$3.27_{\pm 0.31}$	$3.44_{\pm 0.29}$
	CosyVoice2	**1.411**	3.605	0.402	4.535	3.316	0.831	$3.33_{\pm 0.31}$	$2.87_{\pm 0.32}$	$3.31_{\pm 0.28}$
	IndexTTS2	2.454	3.871	0.457	4.465	3.304	**0.861**	$3.20_{\pm 0.36}$	$2.98_{\pm 0.30}$	$\mathbf{4.07}_{\pm 0.26}$
	Ours	2.519	**3.925**	**0.485**	**4.706**	3.395	0.837	$\mathbf{4.00}_{\pm 0.24}$	$\mathbf{4.20}_{\pm 0.23}$	$3.42_{\pm 0.30}$
Chinese	MaskGCT	7.221	3.693	0.350	4.309	3.278	0.814	$2.80_{\pm 0.34}$	$2.33_{\pm 0.31}$	$3.64_{\pm 0.27}$
	F5TTS	10.317	3.314	0.324	3.718	3.228	0.734	$3.22_{\pm 0.36}$	$2.49_{\pm 0.38}$	$3.13_{\pm 0.28}$
	SparkTTS	**3.107**	3.466	0.382	4.338	3.345	0.807	$3.42_{\pm 0.33}$	$2.87_{\pm 0.31}$	$3.80_{\pm 0.24}$
	CosyVoice2	3.375	3.306	0.423	4.147	3.313	0.766	$3.04_{\pm 0.35}$	$2.71_{\pm 0.37}$	$3.29_{\pm 0.29}$
	IndexTTS2	4.015	3.694	0.401	4.146	3.289	**0.869**	$3.67_{\pm 0.33}$	$3.02_{\pm 0.30}$	$\mathbf{3.87}_{\pm 0.24}$
	Ours	3.792	**3.752**	**0.470**	**4.509**	**3.370**	0.724	$\mathbf{4.13}_{\pm 0.23}$	$\mathbf{4.07}_{\pm 0.30}$	$3.62_{\pm 0.32}$
Text Emotion Prompt										
English	CosyVoice2	**1.522**	3.465	0.453	4.330	3.271	0.303	$3.33_{\pm 0.37}$	$3.73_{\pm 0.31}$	$2.53_{\pm 0.31}$
	IndexTTS2	2.246	3.543	0.424	4.299	3.216	**0.525**	$3.76_{\pm 0.39}$	$3.44_{\pm 0.35}$	$3.42_{\pm 0.29}$
	Ours	3.038	**3.694**	**0.462**	**4.569**	**3.335**	0.433	$\mathbf{4.04}_{\pm 0.29}$	$\mathbf{4.22}_{\pm 0.23}$	$\mathbf{3.64}_{\pm 0.31}$
Chinese	CosyVoice2	**4.488**	3.105	**0.477**	4.346	3.206	0.222	$2.18_{\pm 0.33}$	$3.56_{\pm 0.31}$	$2.84_{\pm 0.35}$
	IndexTTS2	6.962	3.212	0.369	4.179	3.169	**0.702**	$3.29_{\pm 0.36}$	$2.71_{\pm 0.33}$	$3.56_{\pm 0.31}$
	Ours	5.893	**3.357**	0.421	**4.407**	**3.295**	0.531	$\mathbf{4.07}_{\pm 0.25}$	$\mathbf{4.04}_{\pm 0.22}$	$\mathbf{3.84}_{\pm 0.25}$

Table 1: Objective and subjective evaluation across different emotion prompt settings. ↓ indicates that lower values are better, while ↑ indicates that higher values are better. Subjective results are evaluated by 15 listeners, with 95% confidence intervals computed using a t-test. The best results are highlighted in **bold**, and the second-best results are underlined.

neutral emotion. In contrast, our method performs multi-segment duration control in a single generation, making SSIM preservation more challenging but better reflecting realistic controllable synthesis scenarios. Overall, these results demonstrate that our training-free framework supports effective intra-utterance emotion and duration control under more challenging settings, while consistently outperforming the baseline and comparative methods on most objective metrics and achieving state-of-the-art transition smoothness.

Subjective Evaluation. We report subjective results on SMOS, NMOS, EMOS, and SPMOS in Tab. 1 and 2. Unlike comparative methods that synthesize segments independently, our approach performs one-shot generation with all intra-utterance emotion and duration variations. Despite being training-free and inherently bounded by the baseline model, our framework achieves state-of-the-art or highly competitive performance across most MOS metrics in both emotion and duration control evaluations.

5.2 Ablation Study

Emotion and Duration Control Evaluation. We evaluate emotion conditioning and duration steering as two segment-level components of our framework. For emotion control, restricting segments to local text only (w/o full-text access) or removing MSA alignment (w/o alignment) degrades expressive quality and cross-segment speaker consistency, as evidenced by reduced DNSM and SSIM in Tab. 3, indicating that full-text access and monotonic alignment primarily contribute to smooth emotional transitions rather than token-level accuracy. For duration control, disabling local steering (w/o local steering) leads to the largest performance drop, while removing global EOS control (w/o global EOS) causes a smaller but consistent degradation, suggesting that local pacing dominates segment-level naturalness and global EOS provides additional stabilization.

Monotonic Stream Alignment Evaluation. To evaluate the effectiveness of MSA, we visualize alignment results under different settings in Fig. 4 and report the mean absolute error (MAE) of segment boundary positions. Raw attention maps exhibit diffuse and locally non-monotonic patterns, making greedy alignment highly sensitive to noise and leading to unstable trajectories and frequent segment switching failures. Introducing the monotonic stream constraint alleviates this issue and reduces MAE to 0.216, but residual attention uncertainty still causes instability. By further incorporat-

	Model	WER/CER↓	DNSM↑	SSIM↑	NISQA↑	OVRL↑	SMOS↑	NMOS↑	SPMOS↑
Speech Emotion Prompt									
English	MaskGCT	2.482	3.964	0.539	4.536	3.301	$4.00_{\pm 0.32}$	$3.42_{\pm 0.38}$	$3.47_{\pm 0.31}$
	F5TTS	**1.941**	3.683	0.543	4.454	3.307	$3.76_{\pm 0.32}$	$3.02_{\pm 0.42}$	$3.24_{\pm 0.32}$
	IndexTTS2	2.597	3.899	**0.575**	4.604	3.273	$3.89_{\pm 0.33}$	$3.87_{\pm 0.32}$	$\mathbf{3.67}_{\pm 0.37}$
	Ours	3.227	**3.988**	0.532	**4.766**	**3.336**	$\mathbf{4.22}_{\pm 0.22}$	$\mathbf{4.20}_{\pm 0.25}$	$3.62_{\pm 0.34}$
Chinese	MaskGCT	8.140	3.711	**0.614**	4.366	3.167	$3.31_{\pm 0.40}$	$2.60_{\pm 0.39}$	$3.02_{\pm 0.31}$
	F5TTS	9.004	3.386	0.598	4.286	3.204	$3.82_{\pm 0.35}$	$2.59_{\pm 0.40}$	$2.89_{\pm 0.36}$
	IndexTTS2	**1.623**	3.715	0.597	4.345	3.248	$3.76_{\pm 0.34}$	$3.27_{\pm 0.34}$	$2.84_{\pm 0.38}$
	Ours	2.732	**3.803**	0.578	**4.536**	**3.291**	$\mathbf{3.98}_{\pm 0.28}$	$\mathbf{4.16}_{\pm 0.27}$	$\mathbf{3.62}_{\pm 0.30}$

Table 2: Objective and subjective evaluation on different duration scaling settings. ↓ indicates that lower values are better, while ↑ indicates that higher values are better. Subjective results are evaluated by 15 listeners, with 95% confidence intervals computed using a t-test. The best results are highlighted in **bold**, and the second-best results are underlined.

Method	WER/CER↓	DNSM↑	SSIM↑	NISQA↑
Segment-aware Emotion Conditioning				
Ours	2.519	**3.925**	**0.485**	**4.706**
w/o full-text access	2.409	3.855	0.449	4.578
w/o alignment	**2.043**	3.831	0.442	4.639
Segment-aware Duration Steering				
Ours	**3.227**	**3.988**	**0.460**	**4.766**
w/o local steering	3.861	3.032	0.437	4.750
w/o global EOS	3.513	3.885	0.451	4.717

Table 3: Ablation study of our segment-aware emotion conditioning and duration steering modules.

Method	*0.75	*0.875	*1	*1.125	*1.25
Ours	3.387	**1.704**	**3.218**	**3.210**	**3.211**
w/o local steering	3.728	3.203	5.670	8.179	11.594
w/o global EOS	**1.941**	2.404	5.638	7.650	9.158
Baseline	5.778	6.912	7.100	8.232	12.032

Table 4: Average semantic token number error rate (%) across segments for duration control under different settings. Lower indicates better duration accuracy.

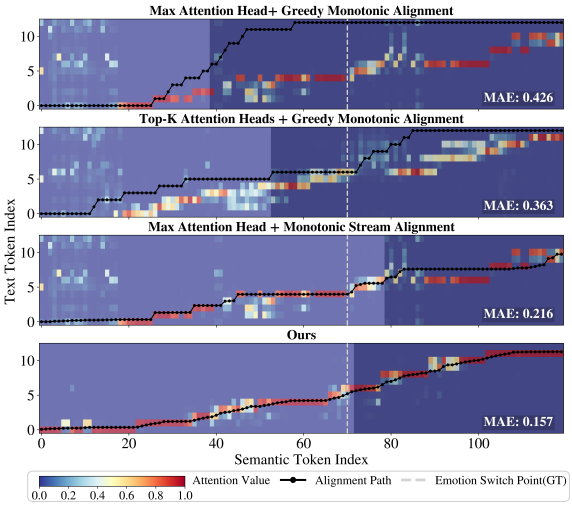

Figure 4: Visualization of alignment paths and emotion switching, with background shading denoting emotion segments and lower MAE indicating better alignment.

ing the observation component, MSA effectively suppresses alignment uncertainty, enforces smooth monotonic trajectories, and reduces MAE to 0.157, yielding precise emotion transitions closely aligned with the ground-truth boundaries.

Duration-Specified Evaluation. We evaluate duration-specified speech synthesis under five segment-level scaling factors (*0.75, *0.875, *1.0, *1.125, and *1.25), comparing our full system with ablated variants and an IndexTTS2 baseline. As shown in Tab. 4, our method consistently achieves the lowest semantic token number error across all settings, reducing the error by 3.53% and 2.41% on average compared to variants without local steering and global EOS control, respectively. Relative to the baseline without explicit duration control, our approach further yields a 5.07% average error reduction, demonstrating accurate and robust duration control across diverse segment-level targets.

6 Conclusion

In this paper, we propose the first training-free controllable framework to enable intra-utterance emotion and duration control in pretrained zero-shot TTS. By introducing segment-aware emotion conditioning and duration steering from an inference-time perspective, our method achieves smooth emotional transitions and temporal regulation within a single utterance. Extensive experiments demonstrate that our method not only delivers state-of-the-art intra-utterance controllability, but also preserves baseline-level speech quality of the underlying TTS model.

Limitations

Despite its advantages, our proposed training-free framework also has several limitations. First, the framework does not explicitly model gradual emotion transitions between adjacent segments. While segment-aware masking and alignment ensure smooth signal-level continuity, emotional variation is controlled in a segment-wise manner rather than through a continuous emotion trajectory, which may limit the representation of intermediate emotional states. Second, the precision of duration control is influenced by the duration representation learned in the pretrained baseline TTS model. Since our approach operates without parameter updates, the duration embedding may not always support strictly linear or fine-grained timing control, particularly under highly expressive or out-of-domain conditions. Future work will investigate training-free or minimally adaptive strategies to better model continuous emotion evolution and duration precision, while preserving the simplicity and generality of the proposed framework.

Ethical Considerations

This work involves the use of large language models to generate a synthetic text dataset for Qwen3 fine-tuning and model evaluation, and therefore shares some general characteristics of LLM-based generation, such as occasional variations in factual precision or stylistic expression. All models and datasets used are publicly available and employed under their respective licenses, and no private or personally identifiable speech data is involved. While intra-utterance-level controllable TTS can benefit expressive speech synthesis and human-computer interaction research, high-fidelity speech generation also entails potential risks if misused, such as speaker impersonation or spoofing of voice-based authentication systems. In practical applications, it is important to incorporate appropriate safeguards, including audio watermarking, output traceability, or dedicated detection models, to facilitate the identification of synthesized speech and discourage unintended or malicious misuse.

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A Automatic Prompt Construction

A.1 LLM-Based Prompting Strategy

MED-TTS is synthesized through a structured LLM-driven pipeline consisting of content generation, segment-level annotation, and manual verification. Specifically, we adopt a two-stage prompting strategy to automatically construct intra-utterance emotion and duration TTS prompts. In Step 1, GPT-4o[1] is prompted to generate 15,000 English and 15,000 Chinese emotion-rich content texts that explicitly exhibit continuous emotional transitions within a single utterance. Each text spans multiple emotional phases drawn from 7 core emotions (*happy, sad, angry, surprised, fearful, disgusted,* and *neutral*), forming either smooth or abrupt emotional progressions rather than a single static emotional state. In Step 2, DeepSeek-Chat [2] is prompted to leverage its strong contextual understanding capability, performing precise semantic decomposition by segmenting the utterance into multiple emotion-specific segments. For each segment, it produces a concise natural language emotion description together with an estimated speaking duration, forming a structured sequence of emotion-duration pairs that directly aligns with the input requirements of controllable TTS systems. Example prompts used in Step 1 and Step 2 are shown in List. 1 and List. 2, respectively.

A.2 Quality Control and Manual Verification

To ensure the reliability of the constructed dataset, we employ a combination of automated validation and manual verification for both Step 1 text generation and Step 2 multi-segment prompt annotation.

At the automated level, we employ validation scripts to enforce strict structural, semantic, and

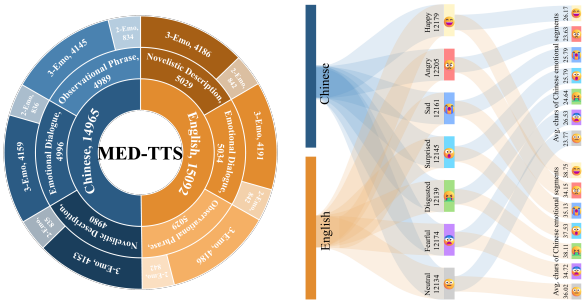
[1] https://openai.com/index/hello-gpt-4o/
[2] https://api-docs.deepseek.com/

distributional constraints. For Step 1 text generation, each sample is verified for valid JSON formatting and required fields, including the text content, text category, and emotion sequence. Specifically, text length is constrained to 15-25 words for English and 15-25 characters for Chinese texts, and each emotion sequence is restricted to 2-3 segments drawn from a predefined set of 7 emotion categories. To reduce redundancy, we remove exact duplicates and filter near-duplicate texts using similarity-based criteria computed from normalized sequence-matching scores between token sequences, applying an overall similarity threshold of 0.85 and an opening similarity threshold of 0.5 over the first few tokens, with similarity comparisons primarily performed among samples sharing the same emotion sequence. For Step 2 multi-segment prompt annotation, automated checks enforce strict alignment between the text and its associated emotion annotations. Specifically, the number and order of segments are required to exactly match the predefined emotion sequence. Each segment must include a valid emotion label, a non-empty natural language emotion description with constrained length (5-25 words for English or 5-30 characters for Chinese), and an estimated speaking duration falling within a predefined range of 0.3-8.0 seconds.

Beyond automated filtering, we conduct manual verification through stratified random sampling of the validated outputs. In total, 1,000 samples are randomly selected for human review, comprising 500 English and 500 Chinese samples. The sampling process is stratified by language, text category, and the number of emotion segments to ensure broad coverage across diverse data conditions. Human reviewers then examine segmentation boundaries, emotion-text alignment, vocal-affect descriptions, and the plausibility of estimated speaking durations to identify subtle issues that may escape rule-based automatic checks. Insights obtained from this process are used to iteratively refine prompting strategies and validation thresholds. The manual verification checklist applied in Step 1 and Step 2 is provided in List 3.

A.3 Dataset Statistics and Distribution

We summarize the statistics and distribution of the MED-TTS dataset across languages, text categories, and emotion segments. As illustrated in Fig. 5a, the dataset is well balanced across languages, comprising 14,965 Chinese and 15,092



(a) Distribution of Content Segments (b) Distribution of Emotion Segments

Figure 5: Statistics of the MED-TTS dataset. (a) Distribution of Chinese and English content segments. (b) Distribution of emotion segments with average character counts.

English samples. Within each language, samples are further evenly distributed across three text categories (vivid descriptions, emotional dialogues, and observational phrases), each contributing approximately 5,000 utterances. A finer-grained breakdown reveals that, within every text category, utterances containing three emotion segments consistently outnumber those with two emotion segments (e.g., roughly 4,100 vs. 800 per category), reflecting a deliberate emphasis on richer intra-utterance emotional transitions. Fig. 5b presents the segment-level emotion statistics. Across both Chinese and English, the 7 emotion types are uniformly represented, with each emotion accounting for approximately 1,200 segments. The average segment length remains stable within each language but differs across languages, with Chinese emotional segments typically spanning about 24-26 characters, while English segments are longer on average, ranging from roughly 34-39 words depending on emotion. Overall, MED-TTS achieves structured balance across languages, text categories, and emotion types, while maintaining sufficient emphasis on multi-emotion utterances to support modeling of continuous intra-utterance transitions.

As illustrated in Tab. 5, we further provide representative examples from the MED-TTS dataset across the three text categories for both Chinese and English. For each language-category pair, the table reports the sample count and total duration, along with illustrative text examples, corresponding emotion sequences, and natural language emotion descriptions. These examples demonstrate that each category consistently includes high-quality samples with different numbers of emotion segments,

Language	Category	Count	Duration(h)	Text Example	Emotion Sequence Example	Emotion Description Example
Chinese	Emotional Dialogue	4,996	9.89	失去你的日子里，心中满是空虚。⇒ 但与你重逢的那一刻，我的笑容重新绽放。	Sad ⇒ Happy	语速缓慢，语调低沉，带有失落和空虚感。⇒ 语速轻快，语调上扬，充满喜悦和温暖。
	Observational Phrase	4,989	10.00	茶杯中水波平静，⇒ 内心却如火山爆发。	Neutral ⇒ Angry	语调平稳，语速适中，声音自然放松。⇒ 语速加快，音调升高，声音紧张有力。
	Vivid Description	4,980	10.05	她无意中推开暗门，⇒ 霉味扑鼻，⇒ 脚步却不敢移动。	Surprised ⇒ Disgusted ⇒ Fearful	语调突然上扬，语速稍快，带有意外感。⇒ 声音压低，语速放缓，带有明显的嫌恶和停顿。⇒ 语调紧张、迟疑，语速缓慢，伴有轻微颤抖。
English	Emotional Dialogue	5,034	9.79	What in the world is that? ⇒ Ugh, it's revolting. ⇒ Well, I suppose it's just another part of life.	Surprised ⇒ Disgusted ⇒ Neutral	Voice rises sharply in pitch, with a quick, breathy delivery. ⇒ Tone is low, guttural, and drawn out with a visceral recoil. ⇒ Pace evens out to a calm, steady, and slightly resigned rhythm.
	Observational Phrase	5,029	9.56	A heated debate burned fiercely, each word adding fuel, ⇒ until playful banter extinguished the flames with lighthearted ease.	Angry ⇒ Happy	Voice is sharp, intense, and rapid, with a clipped, aggressive edge. ⇒ Tone becomes warm, relaxed, and lilting, with a cheerful, flowing cadence.
	Vivid Description	5,029	9.85	A high-pitched scream pierced his thoughts, ⇒ unraveling into a soft sigh, weighted with heartache and longing.	Fearful ⇒ Sad	Voice is sharp, tense, and sudden, with a quick, breathy delivery. ⇒ Tone is slow, breathy, and heavy, with a drawn-out, mournful quality.
Total		**30,057**	**59.14**			

Table 5: Dataset statistics and representative examples across languages and text categories.

highlighting the dataset's coverage of diverse content types and intra-utterance emotional structures across different languages.

A.4 Fine-tuning Details

To enable automatic construction of segment-level TTS prompts, we fine-tune the Qwen3-8B large language model via supervised instruction tuning with parameter-efficient adaptation. We adopt LoRA to update only low-rank adapters while keeping the backbone frozen, thereby preserving general linguistic capabilities. Specifically, fine-tuning is carried out using the SFT-Trainer framework, with LoRA adapters applied to the attention and feed-forward projection layers, using a rank of 32, a scaling factor of 64, and a dropout rate of 0.1. Training is performed for 4 epochs with a per-device batch size of 2 and gradient accumulation over 4 steps, yielding an effective batch size of 8. We use a learning rate of 1×10^{-4} with a linear warmup of 100 steps and enable mixed-precision FP16 training for efficiency.

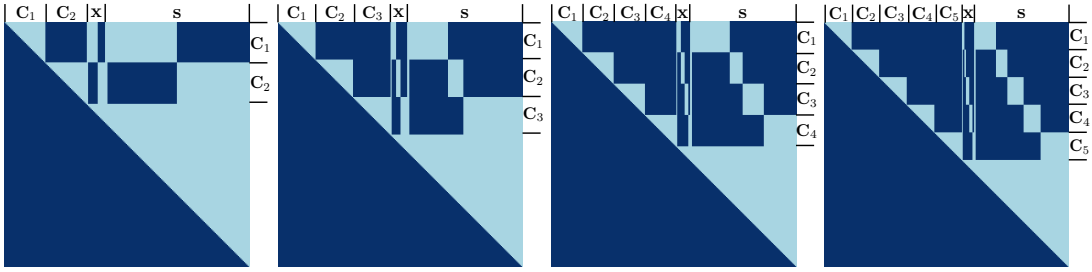
B Segment-Aware Emotion Conditioning

This section provides a brief explanation of the symbols and steps used in Alg. 1.

Inputs and outputs. $\mathbf{x} = \{x_1, x_2, \ldots, x_T\}$ denotes the source text token sequence of length T. $\mathbf{b} = \{b_1, b_2, \ldots, b_M\}$ are segment boundaries on the text timeline, where M is the number of segments. $\mathbf{C} = \{\mathbf{C}_1, \mathbf{C}_2, \ldots, \mathbf{C}_M\}$ are the segment-wise condition embeddings (e.g., emotion/style prompts), and each condition may correspond to a short token span of length L_C in the decoder input. The algorithm autoregressively generates a semantic token stream $\mathbf{s} = \{s_1, s_2, \ldots s_N\}$.

Segment index arrays. $\mathrm{seg}_{\mathbf{x}}[t]$ is the segment id assigned to the t-th text token x_t according to the boundaries. $\mathrm{seg}_{\mathbf{s}}[i]$ stores the segment id used when generating the i-th semantic token s_i. The scalar m denotes the index of the *currently active* segment during decoding and determines which condition embedding is visible to the current generation step.

Step 1: Direct construction of the 2D additive-bias mask $\mathcal{M}_i$. At decoding step i, the decoder input is organized as a single concatenated token list: first all segment conditions, then the full text tokens, and finally the already-generated semantic tokens. Accordingly, the total query/key length is $q = M \times L_C + T + i$. We directly build an additive-bias mask $\mathcal{M}_i \in \mathbb{R}^{q \times q}$, where each entry



(a) $M = 2$ (b) $M = 3$ (c) $M = 4$ (d) $M = 5$

Figure 6: Visualization of the final attention mask under varying numbers of segment conditions (M).

is either 0 (visible) or $-\infty$ (masked). Compared to the previous block-matrix presentation, this version writes all constraints as in-place updates on $\mathcal{M}_i$ with explicit offsets for the condition/text/semantic regions.

- **Standard causal visibility.** We first initialize $\mathcal{M}_i$ and apply a standard causal mask so that each query token can only attend to itself and earlier tokens in the concatenated sequence. This ensures autoregressive consistency for semantic generation.

- **Text-to-condition visibility (segment-local control).** For each text token x_t, we overwrite its attention row to the *condition region* so that x_t can only see the condition tokens belonging to its own segment. Concretely, the entire condition region is masked out for that row, then only the span corresponding to $\mathbf{C}_{\mathrm{seg}_{\mathbf{x}}[t]}$ is unmasked. This prevents text tokens in one segment from reading condition prompts from other segments.

- **Semantic-to-condition visibility (segment-local control).** Similarly, for each previously generated semantic token s_r, we restrict its visibility to the condition region to be segment-local. The semantic token can only attend to the condition tokens of the segment recorded in $\mathrm{seg}_{\mathbf{s}}[r]$. This enforces that past semantic tokens do not leak information from conditions of unrelated segments.

- **Condition-to-condition isolation (no cross-condition leakage).** Condition tokens are not allowed to exchange information across different segments. We therefore mask each condition block's attention to all other condition blocks, keeping only the within-block (diagonal) visibility. This makes each segment condition self-contained while still allowing the overall model to read text/semantic context under the global causal structure.

Step 2: One-step decoding and attention observation. Given $\mathcal{M}_i$, the decoder performs one autoregressive step to produce the next semantic token $\mathbf{s}_i$. During the same forward pass, it also returns the raw attention maps $\mathbf{A}_i$ used as an online alignment observation. After generation, we append s_i to $\mathbf{s}$ and record $\mathrm{seg}_{\mathbf{s}}[i] \leftarrow m$.

Step 3: Monotonic Stream Alignment (MSA). MSA tracks where the semantic stream is aligned on the text in an online manner. It maintains a posterior belief over text positions and advances it with a monotonic prior transition to encourage forward progression. From the returned attentions $\mathbf{A}_i$, the algorithm selects a single layer/head whose attention pattern best matches the prior, optionally smooths it to reduce noise, and fuses it with the prior to obtain a stable posterior belief for the current step. In our implementation, the transition factor in $\mathcal{P}$ is set to $p = 0.1$, and a Gaussian smoothing function $\mathcal{G}_\sigma$ with $\sigma = 1.2$ is applied.

Step 4: Segment switching. The active segment index m is updated by monitoring the expected aligned text position under the current posterior belief. Once this expected position passes the boundary of the current segment, we increment m to trigger an emotion/style switch for subsequent semantic tokens. Overall, this mechanism enforces segment-local control through restricted condition visibility, while preserving global coherence via standard causal decoding and online monotonic alignment.

Mask visualization. Fig. 6 illustrates the resulting mask pattern produced by the direct in-place construction in Step 1 when the utterance is partitioned into different numbers of segments

(M=2, 3, 4, 5). Each panel shows how the condition token blocks, text tokens, and semantic tokens are jointly constrained by (i) the global causal structure and (ii) the segment-local condition visibility. As M increases, the condition region is divided into more isolated blocks, and each text/semantic token is restricted to attend only to the condition block of its assigned (or currently active) segment. This visualization helps verify that the mask enforces local emotion/style control without allowing cross-condition leakage across segments.

C Segment-Aware Duration Steering

In practice, segment-aware duration steering is implemented as two lightweight inference-time controllers that operate entirely on semantic token counts and alignment signals. For local duration steering, a proportional controller described in Section 3.3 performs online correction by comparing the normalized semantic generation progress within the active segment to the normalized text progress obtained from the MSA algorithm. The correction is applied with gain $k_p = 25.0$, which determines the sensitivity of duration adjustment to progress mismatch, and is triggered only when the absolute progress error exceeds $\varepsilon = 0.01$, thereby preventing unnecessary updates caused by minor alignment fluctuations. To ensure stability, updates are performed at a fixed low frequency of one update every five decoding steps, and the per-update adjustment is clamped to a maximum magnitude of $\Delta_{\max} = 10$ semantic tokens to avoid abrupt changes in generation pace. In addition, the effective target is constrained by adaptive lower bounds tied to the current global decoding cursor, with conservative and emergency regimes activated when the generated length exceeds $1.2\times$ and $1.5\times$ the planned segment budget, respectively, serving as a safeguard against uncontrolled over-generation.

For global EOS steering, an EOS controller is added to the logits processor list, where EOS logits are fully suppressed for all non-final segments, while being dynamically adjusted in the final segment based on the ratio between generated semantic tokens and the target semantic budget. Specifically, EOS is strongly suppressed when the ratio is below 0.5, gradually transitions to a neutral region over the interval $[0.8, 1.1]$, and is increasingly encouraged as the ratio approaches 1.2, with the applied bias bounded between -5.0 and $+15.0$. These fixed hyperparameters were selected empirically and remain constant across all experiments, enabling robust intra-utterance duration control without modifying or retraining the underlying TTS model.

D Ablation Models Implementation

D.1 Emotion and Duration Control

In the segment-aware emotion conditioning part of Tab. 3, we compare our method with the following two ablated variants:

- **w/o full-text access**: In this variant, each segment condition can only attend to the local text tokens within its own segment, rather than the full text.
- **w/o alignment**: In this variant, we remove any alignment module and generate semantic tokens by randomly switching phases through a fixed probability at each step.

For the segment-aware duration steering part of Tab. 3, we further evaluate two ablated variants to analyze the contributions of local and global steering mechanisms:

- **w/o local steering**: In this variant, the local duration steering module is disabled, and segment-level pacing relies solely on the baseline duration embedding, while the global EOS control mechanism is retained.
- **w/o global EOS**: In this variant, the global EOS logit modulation is disabled, while the local duration steering module remains active.

D.2 Monotonic Stream Alignment Evaluation

In Fig. 4, we compare our MSA method with the following ablated variants:

- **Max Attention Head + Greedy Monotonic Alignment**: In this variant, we replace our MSA with a deterministic heuristic. We firstly compute a score for each raw attention maps across all layers and heads through $F^{(l,h)} = \frac{1}{T}\sum_{t=1}^{T} \mathbf{A}_{i,t}^{(l,h)}$, where T is the length of text tokens and t is the text position. The optimal attention map (l^*, h^*) is selected as the observation by the maximum score. For the update step, we restrict a monotonic constraint and simplify the posterior $\boldsymbol{\pi}_i$ to a one-hot vector, representing a hard alignment state. Let k be the active index at the previous step, i.e.,

$\boldsymbol{\pi}_{i-1}(k) = 1$, and the update rule follows a greedy local comparison between the current position k and the next position $k+1$. The new belief is determined as:

$$\boldsymbol{\pi}_i(t) = \mathbb{1}\left[t = \underset{m \in \{k, k+1\}}{\arg\max}\ \mathbf{A}_{i,m}^{(l,h)}\right], \quad (4)$$

where $\mathbb{1}[\cdot]$ is the indicator function.

- **Top-k Attention Heads + Greedy Monotonic Alignment**: In this variant, we extend the previous method by selecting the top-k attention heads as observations. Specifically, we first compute the scores $F^{(l,h)}$ for all attention maps and select the top-k heads with the highest scores. The observation is then derived as a weighted average of these selected attention maps based on their scores. The greedy monotonic alignment update remains the same as above.

- **Max Attention Head + Monotonic Stream Alignment**: In this variant, we retain alignment updates using our MSA algorithm. We replace the observation component by selecting a single attention head with the maximum score as described above, and get rid of the smoothing operation.

E Evaluation Protocol

E.1 Baseline and Comparative models

Baseline. IndexTTS2[3] (Zhou et al., 2025) is an autoregressive zero-shot TTS model that supports utterance-level control of emotion and speech duration while maintaining high speech naturalness. It disentangles speaker identity from emotional expression, enabling faithful reconstruction of target timbre and accurate reproduction of the specified emotional style. By incorporating GPT-based latent representations, the model further improves semantic consistency and stability under expressive conditions.

We also adopt several strong zero-shot TTS as our comparative methods:

- **MaskGCT**[4] (Wang et al., 2025c) is a non-autoregressive TTS model that a masked generative transformer to predict semantic and acoustic tokens, functioned with duration control. By leveraging two-stage mask prediction mechanism, it achieves high fidelity and robust voice synthesis.

- **F5TTS**[5] (Chen et al., 2025) is a non-autoregressive TTS system based on Diffusion Transformer (DiT). It eliminates explicit alignment by padding text to speech length. Trained on 100k hours of data, it employs Sway Sampling to achieve efficient, high-quality zero-shot multilingual synthesis.

- **SparkTTS**[6] (Wang et al., 2025b) is a powerful TTS system built upon Qwen2.5, which directly reconstructs audio from LLM-predicted codes and eliminates the need for complex intermediate models like flow matching. It excels in high-fidelity zero-shot voice cloning for bilingual scenarios while maintaining high efficiency.

- **CosyVoice2**[7] (Du et al., 2024b) is an autoregressive TTS model that combines a language model for semantic and prosodic modeling with flow matching for speaker identity reconstruction, utilizing a supervised speech tokenizer to achieve disentangled generation. Notably, it demonstrates superior performance in Chinese compared to English due to its training data distribution.

Our baseline and comparative models adopt a consistent segment-wise inference strategy. Each sentence is partitioned into multiple segments based on target emotions and speaking rates generated by our fine-tuned LLM. These segments are generated individually among these models and sequentially assembled to reconstruct the complete utterance for evaluation. All baseline and comparative models are implemented using their official open-source codebases and pretrained weights.

E.2 Subjective Evaluation

We conduct a subjective Mean Opinion Score (MOS) evaluation focusing on four key dimensions: emotion consistency, speaking rate consistency, speaker similarity, and emotional transition smoothness. Participants were provided with explicit scoring criteria, and we report the mean scores along

[3] https://github.com/index-tts/index-tts
[4] https://github.com/open-mmlab/Amphion/tree/main/models/tts/maskgct
[5] https://github.com/SWivid/F5-TTS
[6] https://github.com/SparkAudio/Spark-TTS
[7] https://github.com/FunAudioLLM/CosyVoice?tab=readme-ov-file

with 95% confidence intervals (CI) in Tab.1 and Tab.2. The evaluation involved 15 graduate students with relevant research backgrounds. Prior to the evaluation, participants were provided with detailed task protocols and informed of the specific usage of the data. Each participant evaluated 18 test samples (9 Chinese and 9 English) under different settings, with the entire session lasting approximately 40 minutes. Scores ranged from 1 to 5 with 1-point intervals. Each participant received compensation of 15 SGD for their participation. The user interface for MOS evaluation is illustrated in Fig. 8.

E.3 Objective Evaluation

Our objective evaluation encompasses several metrics to assess various aspects of speech synthesis quality and controllability. Character accuracy is measured using an automatic speech recognition (ASR) model through comparison with ground-truth transcriptions. For English audio evaluation, we employ a Whisper Large V3 (Radford et al., 2023) ASR model to calculate Word Error Rate (WER)[8], while for Chinese audio, we utilize a Paraformer (Gao et al., 2022) ASR model to calculate Character Error Rate (CER) for Chinese to quantify transcription accuracy[9].

To evaluate the smoothness of transitions in both emotion and speaking rate, we adopt the DNSMOS Pro[10] (Cumlin et al., 2024), referred as DNSM. It is calculated by averaging the predicted MOS values obtained from a sliding window (2-second duration, 1-second stride) applied across the full utterance. Speaker similarity is assessed using fine-tuned WavLM-Large (Chen et al., 2022) for speaker verification[11] to extract speaker embeddings from synthesized and reference audios, followed by computing the cosine similarity, denoted as SSIM. We report the average scores of the two metrics: the similarity between the synthesized and reference audios, and the intra-utterance consistency measured across all segment pairs obtained via ASR-based segmentation within the generated speech.

For speech naturalness evaluation, we utilize NISQA[12] (Mittag et al., 2021) and OVRL from DNSMOS[13] (Reddy et al., 2022) for overall quality of a synthesized sequence. Both of them are evaluated through the entire utterance without segmentation. The emotional expression accuracy is measured through extracting segment-level emotional embeddings from ASR-segmented audio clips using a pre-trained speech emotion recognition model emotion2vec-large[14] (Ma et al., 2024). We calculate the cosine similarity between synthesized and reference audios for in speech prompt settings, and utilize classification accuracy over 5 discrete emotional labels for text prompt settings.

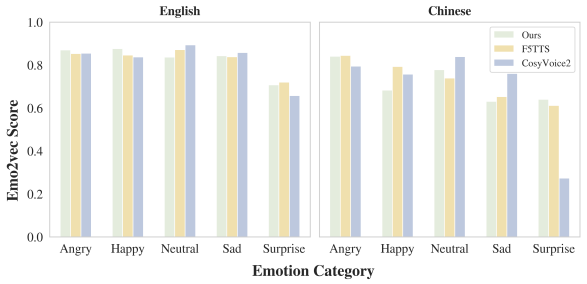


Figure 7: Comparison of Emo2Vec similarity scores across languages for five emotion categories. Our method is compared with F5TTS(Chen et al., 2025) and CosyVoice2(Du et al., 2024b).

E.4 Experimental Result Supplements

Emotion-Specific Control Evaluation. We provide detailed experimental results for the emotional similarity across five discrete categories (Angry, Happy, Neutral, Sad, Surprise). Our results are shown in Fig. 7, highlighting distinct performance patterns across different input modalities. Our method demonstrates robust emotional fidelity, achieving emotional similarity scores that closely approach those of comparative methods. It's worth emphasizing that while other methods could only generate single emotion clips where the global style is constant, our method generates continuous and multi-segment sequences with transitioning emotions. Despite the difficulty of modeling such dynamic emotional control, our model still maintains high emotional similarity, and even superior performance in certain categories such as Angry and Sad, proving its effectiveness in generating complex and varying prosody.

Category-Specific Emotion Control Evaluation.

[8] https://huggingface.co/openai/whisper-large-v3
[9] https://huggingface.co/funasr/paraformer-zh
[10] https://github.com/fcumlin/DNSMOSPro
[11] https://github.com/microsoft/UniSpeech/tree/main/downstreams/speaker_verification
[12] https://github.com/gabrielmittag/NISQA
[13] https://github.com/microsoft/DNS-Challenge/tree/master/DNSMOS
[14] https://huggingface.co/emotion2vec/emotion2vec_plus_large

Prompt	Category	Method	WER↓	DNSM↑	SSIM↑	NISQA↑	OVRL↑	Emo2vec↑
Speech	Emotional Dialogue	MaskGCT	1.978	3.757	0.331	4.375	3.266	**0.862**
		CosyVoice	**0.459**	3.570	0.394	4.403	3.321	0.822
		Ours	5.462	**3.839**	**0.442**	**4.670**	**3.372**	0.811
	Observational Phrase	MaskGCT	4.468	3.849	0.352	4.518	3.277	**0.854**
		CosyVoice	1.021	3.567	0.410	4.515	3.333	0.844
		Ours	**0.834**	**3.903**	**0.491**	**4.710**	**3.418**	0.848
	Vivid Description	MaskGCT	3.612	3.866	0.377	4.463	3.267	0.831
		CosyVoice	**0.834**	3.621	0.443	4.535	3.313	0.826
		Ours	1.085	**3.940**	**0.508**	**4.636**	**3.391**	**0.836**
Text	Emotional Dialogue	CosyVoice	**0.956**	3.450	**0.473**	4.336	3.294	0.369
		IndexTTS2	4.059	3.506	0.399	4.201	3.194	**0.596**
		Ours	5.996	**3.634**	0.387	**4.515**	**3.324**	0.468
	Observational Phrase	CosyVoice	2.582	3.464	0.435	4.385	3.294	0.270
		IndexTTS2	**0.747**	3.531	0.436	4.316	3.220	**0.416**
		Ours	1.104	**3.657**	**0.477**	**4.606**	**3.327**	0.381
	Vivid Description	CosyVoice	1.631	3.483	0.437	4.373	3.284	0.289
		IndexTTS2	1.442	3.511	0.450	4.353	3.235	**0.489**
		Ours	**0.756**	**3.762**	**0.486**	**4.644**	**3.372**	0.393

Table 6: Objective evaluation results on English Speech and Text inputs across different text categories. ↓ indicates that lower values are better, while ↑ indicates that higher values are better. Best results are **bolded**.

Method	DNSM↑	SSIM↑	NISQA↑	OVRL↑	Emo2vec↑
Ours	**3.925**	**0.485**	**4.706**	**3.395**	**0.837**
Max Head + Greedy	3.901	0.443	4.683	3.372	0.803
Top-k + Greedy	3.878	0.442	4.702	3.383	0.815
Max Head + MSA	3.907	0.462	4.697	3.393	0.828

Table 7: Objective Comparison of Different Alignment Strategies. ↑ indicates that higher values are better. Best results are **bolded**.

Tab. 6 extends our evaluation to three distinct synthesis scenarios in our dataset: Emotional Dialogue, Observational Phrase, and Vivid Description. Our method demonstrates a consistent advantage in audio quality, achieving the highest NISQA and OVRL scores in almost all settings. It also excels in naturalness of emotional transitions, as reflected by the DNSM metric, where our method consistently outperforms all methods across different text categories and input modalities. This further confirms that our segment-aware generation effectively maintains naturalistic acoustic synthesis even when handling complex emotional transitions.

Nevertheless, we observe that our method still faces challenges in speaker similarity in certain scenarios. In the text prompt setting, our method lags behind CosyVoice2 in Emotional Dialogue, where the generated sentences often contain extensive emotionally charged and oral conversational elements, such as modal particles and emphatic punctuation. In this scenario, our method and baseline prioritize the expressive prosody, which may lead to deviations from the target speaker's timbre. While CosyVoice2 keeps a more stable and consistent prosody during generation, and preserves speaker identity, it fails to convey the intended emotional expressions. This highlights the inherent trade-off between emotional expressiveness and speaker fidelity in zero-shot TTS, especially when generating highly dynamic prosody from text alone.

MSA Ablation Studies. We further validate the effectiveness of our proposed Monotonic Stream Alignment (MSA) in Tab. 7. We compare our MSA-based alignment strategy against several variants illustrated in Appendix D.2. These protocols are the same as those in Fig. 4. The results show that replacing our MSA with greedy monotonic alignment leads to noticeable performance drops across all metrics, indicating that the MSA mechanism is crucial not just for text-audio synchronization, but also for stabilizing the emotional contents. Through maintaining a robust posterior belief of the current position, MAS prevents the model from drifting off the complex segment boundaries, thereby ensuring the naturalness and coherence of emotional transitions. Notably, even without the full MSA mechanism, these ablation variants still maintain relatively high performance levels. This suggests that synthesizing speech containing multiple com-

plex emotions in a single continuous streaming process, rather than generating each segment independently, inherently preserves semantic and acoustic coherence, which benefits the overall quality of the generated speech.

```
Role:
You are an expert creative screenwriter and emotional expression specialist.
Your task is to generate high-quality text utterances for text-to-speech synthesis evaluation.

Task:
Given an ordered emotion sequence, generate a single-sentence text utterance that reflects
the emotional journey described by the sequence.
The text should naturally transition through these emotions in order.

Emotion Sequence:
1. ${Emotion_1}$
2. ${Emotion_2}$
3. ${Emotion_3}$

Requirements:

1. Text Utterance:
   - Length: 15-25 words (corresponding to 5-10 seconds of speech).
   - The text MUST contain all emotions in the given sequence, each clearly identifiable.
   - Emotional transitions MUST be conveyed through changes in language tone, imagery, internal
     reactions, or perspective.
   - CRITICAL: Do NOT use explicit temporal markers such as "then", "now", "afterward", "at
     first", "later", "next", "suddenly", or "finally".
   - The sentence must be semantically coherent and flow naturally as a single utterance.
   - Avoid clich\'ed or overused expressions, especially as opening phrases.
   - The opening MUST be unique and creative; avoid common narrative patterns.

2. Text Category Constraint:
   ${
   - vivid_descriptive: Vivid descriptive sentences (novel prose style). Example: "Wind whispered
     through the parched cornstalks, its voice fraying like worn silk." |
   - emotional_dialogue: Emotionally charged dialogue excerpts (natural spoken lines). Example:
     "I've asked you three times! Why is the door still locked?" |
   - observational_phrase: Observational phrases (subtle situational commentary). Example: "Rain
     taps the window like it's bruising the glass-rhythmic, insistent, all night."
   }$

3. Output Format:
   Provide your response in the following JSON structure ONLY:
   {
     "text": "<generated single-sentence utterance>",
     "text_category": "${text_category: vivid_descriptive | emotional_dialogue |
     observational_phrase}$"
   }

Examples:

Example 1
${Example:
Vivid Descriptive
Input Emotion Sequence:
1. Happy
2. Surprised
3. Sad
Output:
{
  "text": "Warm light drifts around me, a sudden sharp gust jolts the calm,
           and a muted heaviness settles quietly over my thoughts.",
  "text_category": "vivid_descriptive"
}
}$
...

Now generate a text utterance for the given emotion sequence.
```

Listing 1: Example prompt for generating content text with emotion shifts using GPT-4o.

```
Role:
You are an expert linguistic annotator specialized in emotional prosody for TTS datasets.
Your task is to segment the given sentence into emotion-aligned segments while preserving the exact
original wording.

Task:
Segment the following text into contiguous spans that correspond to the emotions in the sequence.
Each segment must represent a natural linguistic unit and reflect its assigned emotion
through tone, sensory cues, or attitude-NOT through explicit time markers.

Input Text:
${Original text generated in Step-1}$

Emotion Sequence:
1. ${Emotion_1}$
2. ${Emotion_2}$
3. ${Emotion_3}$

Requirements:

1. Segmentation Rules:
   - Produce EXACTLY the same number of segments as emotions in the sequence.
   - CRITICAL: Segments MUST correspond to the emotion sequence IN ORDER.
     The first segment maps to the first emotion, the second to the second emotion, etc.
   - Each segment MUST be a continuous span from the original text.
     Do NOT rewrite, reorder, omit, or add any words.
   - All punctuation marks from the original text MUST be preserved in their exact positions.
   - The concatenation of all segments MUST reconstruct the original text exactly.
   - Segment boundaries should align with natural linguistic or prosodic boundaries
     (e.g., phrase or clause boundaries). Do NOT split inside tight phrases.

2. Emotion Description (for TTS prosody reference):
   - Provide a short vocal-affect description (5-15 words) focusing on auditory qualities.
   - The description should focus on auditory characteristics (e.g., pitch,
     intensity, pacing), not on events or semantics.
   - The description MUST align with the assigned emotion.

3. Speaking Time Estimation:
   - Estimate speaking duration in seconds using the guideline:
     0.18-0.30 seconds per word as a baseline.
   - The estimated duration should also reflect the emotional tone of the segment, as different
     emotions naturally influence speaking pace (e.g., excited or tense delivery tends to be
     quicker, while somber or reflective delivery tends to slow down).
   - The final time MUST be a realistic approximation of how the segment would be delivered aloud.
   - IMPORTANT: The sum of all segment durations MUST fall within 5-13 seconds.
   - Output time values as decimal strings (e.g., "2.4").

Output Format (JSON ONLY):
{
  "original_text": "${original input text}$",
  "segments": [
    {
      "lines_seg": "<text segment>",
      "emotion": "<emotion label from the sequence>",
      "emotion_description": "<vocal-affect description>",
      "time": "<estimated speaking time in seconds>"
    },
    ...
  ]
}

Example:
...

Now generate the segmentation for the given input text and emotion sequence.
```

Listing 2: Example prompt for emotion-aligned segmentation and duration annotation using DeepSeek-Chat.

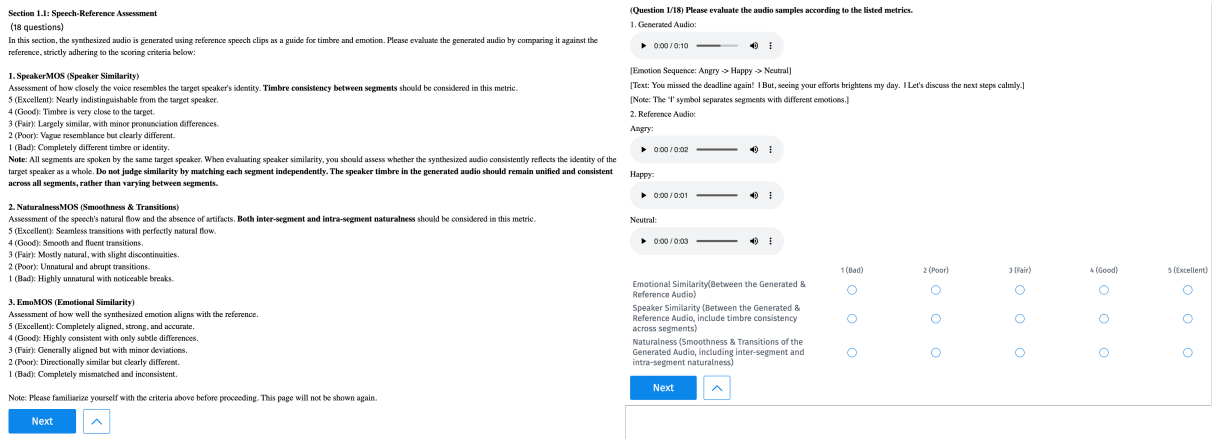
```
Manual Review Checklist (total 1,000 samples: 500 EN / 500 ZH)

----------------------------------------
[Step 1] Content Text Generation

- Text validity:
  the text is complete, fluent, and natural, without obvious truncation, repetition, or unfinished
    clauses (typically a single well-formed sentence).
- Length appropriateness:
  text length falls within the intended range (EN: 15-25 words; ZH: 15-30 characters), and does
    not appear unnaturally compressed or padded to meet length requirements.
- Semantic coherence:
  the text conveys a single coherent idea or situation, rather than a loose collection of phrases
    or unrelated clauses.
- Category consistency:
  the assigned text category matches the content style (vivid descriptive / emotional dialogue /
    observational phrase), with category cues clearly identifiable within the text.
- Emotion sequence correctness:
  the emotion sequence contains 2-3 valid emotions drawn from the predefined set, and all emotions
    are meaningfully reflected somewhere in the text.
- Emotion progression naturalness:
  emotional transitions implied by the text occur in a plausible order, without abrupt or
    logically unsupported emotion jumps.
- Language quality:
  the text does not contain obvious grammatical errors, unnatural phrasing, or machine-like
    constructions that would hinder natural speech rendering.

----------------------------------------
[Step 2] Multi-segment Prompt Annotation

- Segmentation boundaries:
  segment splits occur at natural linguistic or prosodic boundaries, such as phrase or clause
    breaks, and avoid splitting fixed expressions or tight collocations.
- Emotion-text alignment:
  the semantic content of each segment clearly supports its assigned emotion, and the intended
    emotion is perceivable without relying on the description.
- Vocal-affect specificity:
  emotion description includes concrete auditory cues (e.g., energy level, pitch tendency,
    speaking rate, intensity) rather than abstract emotion names.
- Description naturalness:
  emotion description reads as a natural speaking instruction and typically spans one short phrase
    or sentence, rather than a list of keywords.
- Duration plausibility:
  estimated speaking durations are reasonable given segment length and linguistic complexity, and
    fall within the expected range of 0.3-8.0 seconds per segment.
- Duration consistency:
  duration differences across segments reflect intuitive pacing differences, such as faster
    delivery for excited emotions and slower delivery for calm or reflective ones.
- Coverage consistency:
  concatenated segment texts fully reconstruct the original text, with no missing, duplicated, or
    reordered content.

----------------------------------------
Manual Review Protocol

- Reviewers:
  all sampled items are independently inspected by at least two reviewers, covering both English
    and Chinese samples.
- Disagreement handling:
  cases with inconsistent judgments are discussed and resolved through consensus review, and
    recurring issues are recorded for prompt or rule refinement.
```

Listing 3: Manual verification checklist used in our human review process for Step 1 and Step 2 outputs.

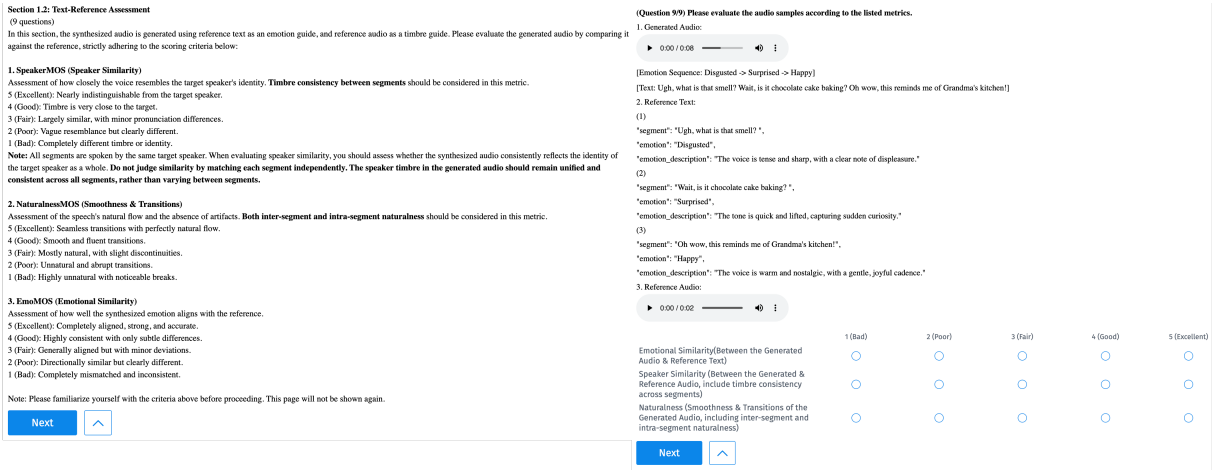
Algorithm 1 Segment-Aware Emotion Conditioning with Monotonic Stream Alignment (MSA)

Input : Text tokens $\mathbf{x} = \{x_1, x_2, \ldots, x_T\}$, segment boundaries $\mathbf{b} = \{b_1, b_2, \ldots, b_M\}$, condition embeddings $\mathbf{C} = \{\mathbf{C}_1, \mathbf{C}_2, \ldots, \mathbf{C}_M\}$
Output : Generated semantic tokens $\mathbf{s} = \{s_1, s_2, \ldots, s_N\}$

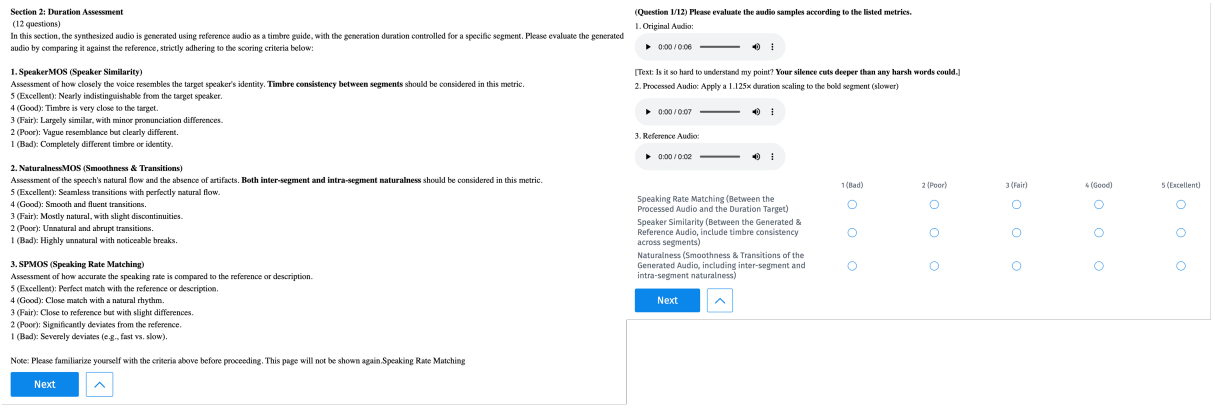
```
// Compute segment id for text tokens seg_x[1..T]:
for t ← 1 to T do
    seg_x[t] ← 1 + Σ_{r=1}^{M-1} I[t > b_r]
end
Initialize seg_s ← [ ]                                   // store segment id for each generated semantic token
Initialize semantic index i ← 0, segment index m ← 1, s ← ∅  Initialize posterior alignment belief π_0 ∈ R^T (one-hot at t = 1)
while not EndOfSentence do
    i ← i + 1
    // 1) Build 2D additive-bias offset mask directly on M_i
    q ← M × L_C + T + i                                  // #Q tokens: [C_{1:M}, x_{1:T}, s_{1:i}]
    M_i ← (−∞) · 1_{(q)×(q)}
    // 1.1) Standard causal mask
    for u ← 1 to q do
        for v ← 1 to u do
            M_i[u, v] ← 0
        end
    end
    // 1.2) x -> C: Text tokens to condition embeddings (segment-local condition visibility)
    off ← M × L_C
    for t ← 1 to T do
        M_i[off + t, 0 : M × L_C] ← −∞
        M_i[off + t, L_C × (seg_x[t] − 1) : L_C × seg_x[t]] ← 0
    end
    // 1.3) S -> C: Semantic tokens to condition embeddings (segment-local condition visibility)
    off ← M × L_C + T
    for r ← 1 to i − 1 do
        M_i[off + r, 0 : M × L_C] ← −∞
        M_i[off + r, L_C × (seg_s[t] − 1) : L_C × seg_s[t]] ← 0
    end
    // 1.4) C -> C: Condition embeddings to condition embeddings (no cross-condition leakage)
    for u ← 1 to M do
        M_i[(u − 1) × L_C : u × L_C, 0 : M × L_C] ← −∞
        M_i[(u − 1) × L_C : u × L_C, (u − 1) × L_C : u × L_C] ← 0
    end
    // 2) Decode one step with mask and get raw attentions as observation
    (s_i, A_i) ← f_θ^{decode-step}(x, s_{<i}, {C_j}_{j=1}^M, M_i, return_attn = True)
    s ← {s, s_i}
    seg_s[i] ← m
    // 3) MSA: Predict-Select-Update
    π̂_i ← π_{i−1} · P                                   // Predict (Prior)
    (l*, h*) ← arg max_{l,h} π̂_i^⊤ log(A_i^{(l,h)})
    a* ← G_σ(A_i^{(l*,h*)})                              // Select (Observation)
    π_i ← (π̂_i ⊙ a*) / Z                                 // Update (Posterior)
    // 4) Segment switching via expected aligned position
    if m < M and Σ_{t=1}^T t · π_i[t] > b_m then
        m ← m + 1                                        // Trigger emotion switch
    end
end
return s
```



(a) Speech-Prompted Emotion Control Evaluation



(b) Text-Prompted Emotion Control Evaluation



(c) Duration Control Evaluation

Figure 8: User interface for MOS evaluation across different evaluation tasks.