

RLAIF-SPA: OPTIMIZING LLM-BASED EMOTIONAL SPEECH SYNTHESIS VIA RLAIF

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ABSTRACT

Text-To-Speech synthesis has achieved near-human quality in neutral speech, but emotional expressiveness remains a challenge. Existing methods often rely on costly emotion annotations or optimize indirect objectives that fail to capture the emotional expressiveness and perceptual naturalness of speech, leading to generated speech that is accurate but emotionally flat. To address these challenges, we propose the **RLAIF-SPA** framework, incorporating a Reinforcement Learning from AI Feedback (RLAIF) mechanism to employ Automatic Speech Recognition (ASR) and Large Language Model (LLM) techniques to respectively judge semantic accuracy and prosodic-emotional label alignment as a direct reward for emotional expressiveness and intelligibility optimization. Specifically, it leverages *Prosodic Label Alignment* to enhance expressive quality by jointly considering semantic accuracy and prosodic-emotional alignment along four fine-grained dimensions: *Structure*, *Emotion*, *Speed*, and *Tone*. In addition, it incorporates *Semantic Accuracy Feedback* to ensure the generation of clear and accurate speech. Experiments on the LibriSpeech dataset show that RLAIF-SPA outperforms Chat-TTS, with a 26.1% reduction in WER, a 9.1% increase in SIM-O, and over 10% improvement in human evaluation.

Index Terms— Emotional Speech Synthesis, Reinforcement Learning, AI Feedback

1. INTRODUCTION

Recent advancements in Text-To-Speech (TTS) synthesis have enabled the generation of speech with near-human quality in neutral styles [1–3]. Nevertheless, human interaction is not solely about informational exchange but also involves the subtle expression of emotion. These emotional signals profoundly impact listener engagement and understanding, a factor of particular consequence in applications like conversational agents, audiobooks, and virtual assistants. In such contexts, a lack of emotional expressiveness can result in speech that sounds monotonous or flat, thereby diminishing its effectiveness [4]. Therefore, TTS models with controllable emotional capabilities play a crucial role in bridging this gap and have become a major focus of research.

Early approaches to emotional TTS often rely on using explicit, coarse-grained emotion labels as conditional inputs to guide the synthesis process [5–7]. These models learn to associate discrete labels with specific acoustic features, such as adjusting pitch and speed to reflect a target emotion [8]. While these techniques provide some levels of control, they have notable limitations. First, discrete emotion labels drastically oversimplify the vast and nuanced spectrum of human expression, failing to capture subtle emotional variations.

Second, creating large-scale, high-quality datasets with manual emotion annotations is prohibitively expensive and time-consuming, hindering model scalability and performance on the emotional speech synthesis task [9–12].

To overcome these constraints, recent work has adopted Reinforcement Learning (RL) to directly optimize perceptual objectives from human feedback [13–15]. By training on pairwise preference data, these models learn human preferences for emotional expression, generating more nuanced and varied speech without relying on predefined labels [16–18]. However, these RL-based methods introduce their own challenges. Relying on extensive human feedback is costly and time-consuming, and the subjective nature of emotional preferences often results in noisy, unreliable reward signals. Moreover, the optimization target is typically a single, holistic preference score. This score assesses overall quality but fails to provide distinct feedback on individual prosodic attributes like rhythm, pitch, and pace. Consequently, these RL-based model lacks the fine-grained control to optimize the emotional speech synthesis models for precise and targeted emotional expression.

To address these challenges, we propose **RLAIF-SPA**¹, a framework that incorporates a **Reinforcement Learning from AI Feedback (RLAIF)** [19] mechanism for **Semantic-Prosodic Alignment** into Text-To-Speech synthesis. Our approach jointly optimizes emotional expressiveness and intelligibility without manual annotations or preference scoring by enabling the model to generate its own reward signals. Specifically, RLAIF-SPA leverages two core components for AI Feedback. First, for expressiveness, it employs *Prosodic Label Alignment*, where the model’s output is judged against automatically generated labels along four fine-grained dimensions: *Structure*, *Emotion*, *Speed*, and *Tone* [20, 21]. This provides a structured, detailed, and consistent reward for emotional quality, directly addressing the need for fine-grained control. Second, for clarity, it uses *Semantic Accuracy Feedback*, which assesses the consistency between the transcribed output and the original input text. By combining these two signals, the AI Feedback mechanism provides a stable and highly scalable optimization target. Experimental results on the LibriSpeech and ESD datasets demonstrate the effectiveness of RLAIF-SPA in both enhancing speech intelligibility and emotional expressiveness. Specifically, RLAIF-SPA significantly reduces word error rate compared to strong baseline models, while also achieving higher speaker similarity and improved emotional alignment.

2. METHODOLOGY

This section details the proposed RLAIF-SPA framework. We first outline the overall training strategy and optimization objective, then elaborate on the two core components of our AI Feedback mecha-

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¹The code is available at <https://github.com/Zoe-Mango/RLAIF-SPA>.

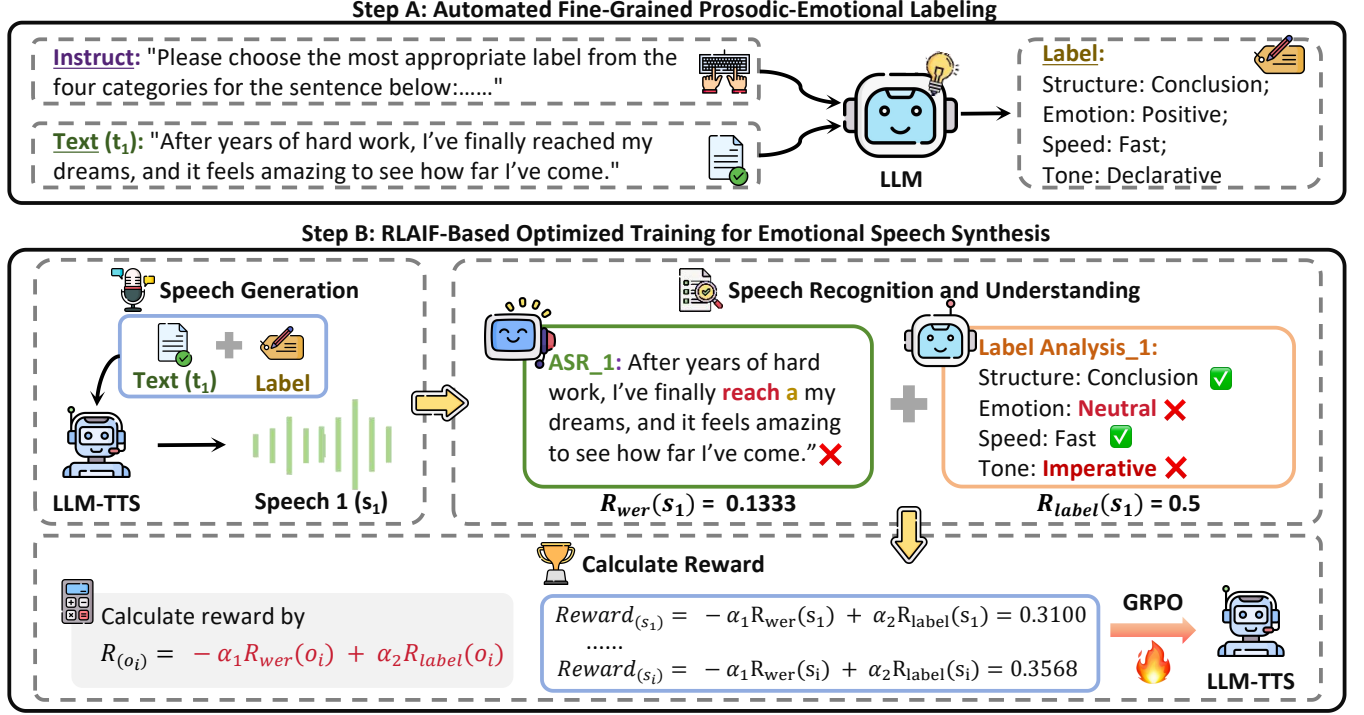


Fig. 1: Illustration of the proposed RLAIF-SPA framework. RLAIF-SPA optimizes both emotional expressiveness and intelligibility through the AI Feedback mechanism, which is generated by AI models themselves.

nism: Prosodic Label Alignment and Semantic Accuracy Feedback, as illustrated in Fig. 1.

2.1. Training Strategy and Optimization Framework

The optimization process of RLAIF-SPA can be formulated as a multi-objective optimization problem, which is guided by AI Feedbacks. Both feedback signals are from two key objectives: emotional expressiveness and speech intelligibility. Our primary goal is to enhance prosodic-emotional label alignment while concurrently minimizing the Word Error Rate (WER), thereby producing speech that is both emotionally expressive and highly intelligible.

Given an input text t_i , the policy model generates a speech sample s_i . This sample is then evaluated using a composite reward function, $R(s_i)$, which balances two key objectives. The first objective, prosodic-emotional alignment, is assessed through a form of speech understanding, while the second, intelligibility, is measured via automatic speech recognition. The reward is computed as a weighted linear combination of the two optimization objectives:

$$R(s_i) = -\alpha_1 R_{wer}(s_i) + \alpha_2 R_{label}(s_i), \quad (1)$$

where $R_{label}(s_i)$ is the reward for prosodic-emotional alignment (Sections 2.2), and $R_{wer}(s_i)$ is a penalty term based on the WER of the generated speech (Section 2.3). The non-negative hyperparameters α_1 and α_2 balance the trade-off between expressiveness and intelligibility.

To optimize our policy model, we adopt Group Relative Policy Optimization (GRPO) [22], which evaluates the relative quality of multiple candidates within a group of generated outputs, rather than assessing each output in isolation. This group-wise comparison is particularly effective for the nuances of speech synthesis. Unlike methods that rely on noisy absolute reward scores or simple binary

preferences, GRPO can better leverage the subtle, multi-dimensional feedback from our prosodic-emotional labels, allowing the model to learn complex trade-offs, such as preferring a speech sample with superior emotional tone over one that is rhythmically perfect but emotionally flat. By integrating GRPO with our AI Feedback mechanism, RLAIF-SPA can effectively optimize both emotional depth and intelligibility. This provides a robust framework for policy refinement that relies on group-relative feedback, leading to a stable, efficient, and low-supervision training process.

Within the GRPO framework, for a given input text t , the policy π_θ generates a group of G candidate speech outputs $\{s_i\}_{i=1}^G$. The model's parameters θ are then updated to maximize the following objective function:

$$J_{GRPO}(\theta) = \mathbb{E}_{q \sim D, \{s_i\}_{i=1}^G \sim \pi_{\theta_{old}}(\cdot|t)} \left[\frac{1}{G} \sum_{i=1}^G L_i(\theta) \right] - \beta D_{KL}(\pi_\theta \parallel \pi_{\theta_{old}}), \quad (2)$$

where $L_i(\theta) = -A_i^G \log P(s_i|t; \theta)$ is the loss for the i -th candidate output. It is the negative log-likelihood of the sample, weighted by its relative advantage A_i^G , which measures the performance of sample s_i relative to the average quality of the group. The term $D_{KL}(\pi_\theta \parallel \pi_{\theta_{old}})$ is a KL divergence penalty that regularizes the policy update, preventing large deviations from the previous policy $\pi_{\theta_{old}}$ and ensuring training stability. The hyperparameter β controls the strength of this regularization.

2.2. Prosodic Label Alignment

The first component of the AI Feedback mechanism is prosodic-emotional label matching. To guide the model toward generating emotionally expressive speech, we adopt a fine-grained labeling

strategy that annotates speech along four distinct prosodic-emotional dimensions: *Structure*, *Emotion*, *Speed*, and *Tone*. These four labels represent key and complementary aspects of emotional expression, thereby forming a comprehensive yet manageable framework. The *Structure* label guides the model in capturing the organization and rhythm of speech—for example, distinguishing between questions and statements or modeling emotional progression in the narrative [23, 24]—thereby enabling the generation of speech that is both emotionally varied and contextually coherent. The *Emotion* label serves as the core determinant of the overall emotional state (e.g., happy, sad) [25]. Meanwhile, *Speed* and *Tone* provide fine-grained control over prosodic characteristics that reflect emotional intensity and color. In detail, *Speed* adjusts the delivery pace, a strong indicator of arousal (e.g., faster for excitement, slower for sadness) [26], while *Tone* controls pitch variation, which is crucial for conveying subtle emotional nuances like the rising intonation in a surprised voice [27, 28].

To implement this strategy at scale, we employ an automated labeling process where a LLM generates the target prosodic-emotional labels for the entire training dataset. This method bypasses the need for costly and time-consuming manual annotation, ensuring efficient and consistent labeling across large volumes of data. During the AI Feedback phase, the model’s generated speech is evaluated for alignment with these LLM-generated target labels. A reward is granted when the predicted prosodic characteristics match the ground truth labels, thereby guiding the model toward producing more emotionally expressive and accurate speech. The reward function for this prosodic-emotional label alignment is formally defined as:

$$R_{\text{label}}(s_i) = \sum_{k=1}^4 w_k \cdot m_k(s_i), \quad (3)$$

where $m_k(s_i)$ is a binary function indicating a match for each of the four prosodic-emotional labels (*Structure*, *Emotion*, *Speed*, and *Tone*), and w_k is the corresponding weight for each label dimension.

2.3. Semantic Accuracy Feedback

The second key component of the AI Feedback mechanism is designed to ensure speech intelligibility. This is achieved by quantifying the semantic accuracy of the synthesized speech. Let t_i be the original input text and s_i be a generated speech sample. We employ an Automatic Speech Recognition (ASR) model to obtain the transcription $ASR(s_i)$.

The intelligibility-driven reward component, R_{wer} , is then formulated as the WER computed between the original text t_i and the transcribed text $ASR(s_i)$:

$$R_{\text{wer}}(s_i) = \text{WER}(t_i, ASR(s_i)), \quad (4)$$

where the $\text{WER}(t_i, ASR(s_i))$ function calculates the standard word error rate between the two input texts. This value serves as a direct cost within our composite reward function (Eq. 1), effectively penalizing any deviation from the source text. By integrating this semantic accuracy penalty, the framework ensures that any improvements in emotional expressiveness do not come at the expense of clarity or content accuracy, leading to speech that is both articulate and emotionally resonant.

3. EXPERIMENTAL METHODOLOGY

In this section, we describe the datasets, baseline, experimental details and evaluation metrics in our experiments.

Datasets and Baselines. Our model is trained on a subset of 1,000 utterances from the LibriSpeech dataset [29], which we annotate with four prosodic-emotional labels (*Structure*, *Emotion*, *Speed*, *Tone*) using GPT-4o. This targeted set is strategically chosen to demonstrate the data efficiency of our reward-based optimization for learning emotional alignment. For a comprehensive evaluation, we test on two datasets: the LibriSpeech test-clean set for general speech quality and the ESD dataset [30] for targeted emotional analysis. The ESD, while smaller, is more emotionally expressive, containing data from 10 speakers across 5 emotions. We compare RLAIF-SPA against two strong, publicly available baselines: MegaTTS3² and Chat-TTS³.

Experimental Setup. Our backbone LLM is based on the MiniCPM-O 2.6⁴ framework. It employs a Whisper-Medium-300M encoder as the speech tokenizer to generate latent representations, Qwen2.5-7B-Instruct as the core LLM, and a Chat-TTS vocoder as the speech detokenizer. We fine-tune the model using GRPO with our AI Feedback mechanism to enhance emotional expressiveness. The reward signal is computed automatically: Whisper-Large-v3⁵ calculates the WER for intelligibility, while Qwen2-Audio⁶ assesses alignment with our four prosodic-emotional labels. The weights for the WER penalty and label reward are set to $\alpha_1 = 0.3$ and $\alpha_2 = 0.7$, with uniform weights (w_k) applied across all label dimensions. To ensure consistency, all components are initialized from their pre-trained MiniCPM-O 2.6 checkpoints. The model is trained for 7 epochs.

Evaluation Metrics. We evaluate our model’s performance using a combination of objective and subjective metrics to assess both intelligibility and emotional expressiveness. For objective assessment, we measure three key aspects. To assess intelligibility, we compute the Word Error Rate (WER) by transcribing the synthesized speech with Whisper-Large-v3 and comparing it to the original text. We use the WavLM-Large [31] model to calculate Speaker Similarity (SIM-O) between the generated sample and the prompt, where a higher score in the range of $[-1, 1]$ indicates greater similarity. Finally, speech emotion recognition is evaluated using the emotion2vec model [32] to verify the accuracy of the generated emotion categories. For subjective evaluation, we conduct human listening tests. We measure speech naturalness using the Mean Opinion Score (MOS), specifically assessing CMOS for overall quality (clarity, naturalness, and high-frequency details) and Emotion MOS for the similarity of emotion between the generated and ground-truth audio. For these tests, 40 random samples were evaluated by at least 20 participants each. Additionally, we conduct AB Preference Tests, asking 20 listeners to select the better sample between RLAIF-SPA and the baselines (Chat-TTS, MegaTTS3) based on emotional expressiveness and overall quality.

4. EXPERIMENTAL RESULTS

4.1. Effectiveness of LLM-TTS Optimized Using RLAIF-SPA

We evaluate the effectiveness of RLAIF-SPA by comparing it against two strong baselines, Chat-TTS and MegaTTS3. Table 1 summarizes the comparative performance of the models, detailing the re-

²<https://github.com/bytedance/MegaTTS3>

³<https://github.com/2noise/ChatTTS>

⁴<https://huggingface.co/openbmb/MiniCPM-o-2.6>

⁵<https://github.com/openai/whisper>

⁶<https://github.com/QwenLM/Qwen2-Audio>

Table 1: Objective and Subjective Evaluation Results Comparison of RLAIIF-SPA with Baselines on WER, SIM-O, CMOS, Emotion MOS, and Speech Emotion Recognition across Two Datasets.

Model	Objective		Subjective		Speech Emotion Recognition				
	WER↓	SIM-O↑	CMOS↑	Emotion MOS↑	Neutral↑	Happy↑	Sad↑	Angry↑	Surprised↑
<i>LibriSpeech test-clean (En)</i>									
Chat-TTS	7.85	0.66	3.56	3.43	0.51	0.21	0.11	0.01	0.03
MegaTTS3	6.90	0.71	3.83	3.82	0.72	0.18	0.26	0.03	0.00
RLAIIF-SPA	5.80	0.72	3.98	3.86	0.77	0.43	0.29	0.01	0.03
<i>ESD (Zh)</i>									
Chat-TTS	6.89	0.70	3.87	3.71	0.76	0.56	0.19	0.01	0.03
MegaTTS3	5.26	0.72	4.02	3.78	0.81	0.36	0.24	0.00	0.03
RLAIIF-SPA	4.01	0.74	4.16	3.90	0.78	0.47	0.33	0.01	0.09

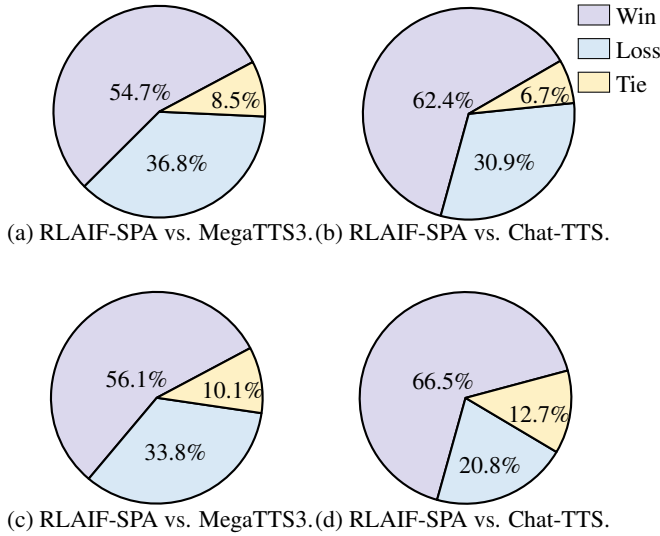


Fig. 2: Comparison of AB Preference Test results on the LibriSpeech dataset ((a), (b)) and the ESD dataset ((c), (d)). Proportions of Win (RLAIIF-SPA preferred), Loss (baseline preferred), and Tie are shown for each comparison.

sults from both objective (WER, SIM-O) and subjective (CMOS, Emotion MOS) evaluation metrics.

As shown in the results, RLAIIF-SPA significantly outperforms both baselines in terms of WER. This substantial improvement in intelligibility is a direct consequence of our methodology, which explicitly incorporates a WER-based penalty into the AI Feedback mechanism. By directly optimizing for semantic accuracy alongside emotional expressiveness, our model is guided to produce speech that is not only emotionally rich but also highly intelligible and precise in its articulation.

Beyond intelligibility, RLAIIF-SPA excels in emotional expressiveness and overall speech quality. This advancement is principally driven by our fine-grained, label-driven reward component, which enables the model to precisely modulate prosodic nuances across four dimensions: Structure, Emotion, Speed, and Tone. The model’s superiority is validated through a suite of evaluations. Objectively, it achieves higher speaker similarity (i.e., SIM-O) and greater accuracy in automatic speech emotion recognition, confirming that the synthesized emotions are distinct and well-aligned with their targets. Subjectively, listeners award RLAIIF-SPA higher ratings for both overall quality (i.e., CMOS) and emotional fidelity (i.e., Emotion MOS). These findings are corroborated by AB preference tests (Fig. 2), in

which a significant majority of participants prefer RLAIIF-SPA for its compelling balance of clarity and rich emotional nuance.

4.2. Ablation Study

To isolate and verify the contributions of the key components within our framework, we conduct an ablation study, with results presented in Table 2. We examine two variants of our model: one without the GRPO strategy and another without the fine-grained label rewards.

Removing the GRPO component leads to a substantial increase in WER and a drop in speaker similarity. The reason may lie in that GRPO provides a stable learning signal by evaluating the relative quality of candidates within a group. Since the rewards are derived from AI feedback, optimizing without GRPO relies on synthesized, noisy and high-variance signals from individual samples, resulting in unstable policy updates and hindering consistent convergence. This instability directly degrades the model’s ability to maintain articulatory precision and timbral consistency, thus causing the higher WER and lower speaker similarity. Similarly, removing the prosodic-emotional label rewards also results in significant performance degradation. This occurs because, without these fine-grained rewards, the optimization objective defaults to minimizing WER alone. Consequently, the model tends to generate highly intelligible but emotionally monotonous speech, lacking the guidance necessary to modulate prosody across the critical dimensions of Structure, Emotion, Speed, and Tone.

Table 2: Ablation Study on Model Performance.

Model	WER↓	SIM-O↑	CMOS↑	Emotion MOS↑
RLAIIF-SPA	5.80	0.72	3.98	3.86
w/o GRPO	11.32	0.65	3.51	3.40
w/o label	8.89	0.63	3.60	3.17

5. CONCLUSION AND FUTHER WORK

This paper presents RLAIIF-SPA, a novel framework that autonomously optimizes for both emotional expressiveness and intelligibility in speech synthesis. By employing a AI Feedback mechanism with GRPO to enforce fine-grained prosodic consistency and semantic accuracy, RLAIIF-SPA significantly outperforms strong baseline models on the LibriSpeech and ESD datasets. Crucially, our work demonstrates the feasibility of generating emotionally rich and highly intelligible speech without reliance on costly manual annotations, paving the way for more scalable and data-efficient emotional TTS systems. Future work will focus on refining the reward mechanism and assessing the framework’s scalability across a broader range of acoustic environments and languages. Another promising direction involves modeling how a speaker’s transient emotional state dynamically shapes prosody.

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