Data-efficient Targeted Token-level Preference Optimization for LLM-based Text-to-Speech

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Abstract

Aligning text-to-speech (TTS) system outputs with human feedback through preference optimization has been shown to effectively improve the robustness and naturalness of language model-based TTS models. Current approaches primarily require paired desirable and undesirable samples at the utterance level. However, such pairs are often limited in TTS output data, and utterance-level formulation prevents fine-grained token-level optimization needed for accurate pronunciation alignment. In this study, we propose TKTO that eliminates the need for paired data, enabling a more data-efficient training paradigm, and directly targets token-level units, automatically providing fine-grained alignment signals without token-level annotations. TKTO improves the challenging Japanese TTS accuracy by 39% and reduces CER by 54%, automatically assigning 12.8× stronger reward to targeted tokens.

1 Introduction

Recent advances in neural network technology have enabled high-fidelity text-to-speech (TTS) synthesis models (Chen et al., 2025; Meng et al., 2025; Li et al., 2024). They typically convert input text into a phoneme sequence using a grapheme-to-phoneme (G2P) converter (Oura et al., 2010), followed by generative models from the phoneme sequence (Wang et al., 2025b; Nishimura et al.). However, G2P is generally based on morphological analysis, and thus may fail to generate correct pronunciations in ambiguous languages like Japanese, where the reading and meaning of words can change depending on context (Figure 1).

G2P-free large language model (LLM)-based TTS methods (Wang et al., 2025a; Du et al., 2024) have shown great promise to generate context-aware pronunciations directly from raw text without G2P by leveraging large-scale natural language pretraining. Recent work (Zhang et al., 2025; Tian et al., 2025; Zhang et al., 2024) has further applied Direct Preference Optimization (DPO) (Rafailov et al., 2023) to improve intelligibility, speaker similarity, and overall naturalness by enlarging the preference gap between pairwise samples.

	Input text	Reading
(a)	このカレーは辛い (This curry is spicy)	karai (spicy)
(b)	この作業は辛い (This work is hard)	tsurai (hard)

Figure 1: Examples of ambiguity in Japanese. Although (a) and (b) contain the same word, its meaning and reading differ depending on the context.

Despite these advances, two fundamental challenges remain. **(i) Necessity of paired data:** DPO-based methods require paired desirable and undesirable outputs for the same utterance, but TTS systems often produce one-sided results, where many samples are consistently desirable or undesirable. This causes significant data inefficiency and wastes costly human feedback, limiting the scalability of DPO-based preference alignment. **(ii) Sample-level optimization:** Pronunciation generation is essentially a character- or token-level task, while preference alignment is conducted with utterance-level labels. This mismatch forces the model to optimize at the data-sample level rather than directly at the pronunciation unit level, leading to suboptimal learning signals and limiting the effectiveness of alignment.

To address these challenges, we propose a novel preference optimization framework, **Token-level Kahneman-Tversky Optimization (TKTO)** that constructs contrastive LLMs to estimate token-level weights and optimizes token-level preferences grounded in Kahneman-Tversky's prospect theory (Ethayarajh et al., 2024). Our contributions are summarized in three key dimensions:

- **Problem formulation:** we pioneer the challeng-

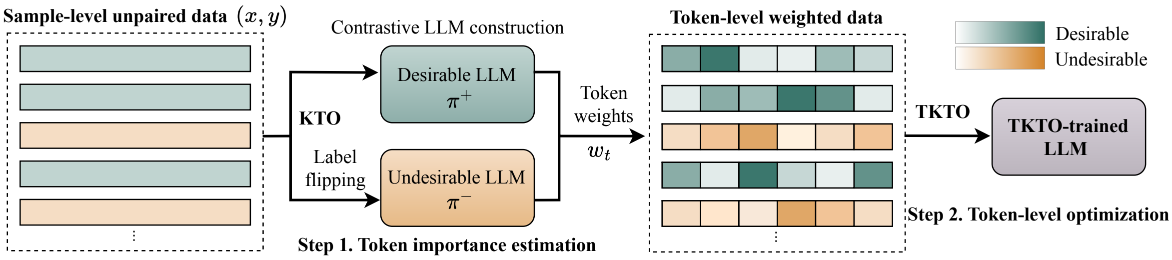


Figure 2: Overview of our TKTO framework. Step 1: we estimate token-level importance weights, constructing two contrastive LLMs. Step 2: we optimize token-level preferences.

ing task of ambiguous Japanese pronunciation as a token-level preference optimization problem.

- **Novel methodology:** we propose TKTO that (i) eliminates the need for paired data, enabling a more data-efficient training paradigm, and (ii) directly targets token-level units, automatically providing fine-grained alignment signals.
- **Wide evaluation:** we demonstrate that TKTO not only reduces character error rate (CER) by 54% but also improves the accuracy of Japanese pronunciation by 39 %, surpassing industry models. It selectively increases the generation probability of desirable tokens and assigns 12.8× stronger rewards to targeted tokens.

2 LLM-based Text-to-Speech

We consider a text-to-speech (TTS) task formulated as conditional generation from input text x to output speech token sequence $y = (y_1, \dots, y_T)$. Let $\pi_\theta(y \mid x)$ denote a LLM decoder that autoregressively predicts acoustic tokens conditioned on textual input and previously generated tokens:

$$\pi_\theta(y \mid x) = \prod_{t=1}^{T} \pi_\theta(y_t \mid x, y_{<t}). \tag{1}$$

The output token sequence y is transformed into speech audio via a neural vocoder. Our goal is to train the LLM decoder π_θ to learn *token-level preferences* from user feedback or preference data.

3 Proposed Method

We propose a two-step approach to optimize token-level preferences from unpaired data (Figure 2). First, we quantify how informative each token is for preference learning. These weights are then used to guide our TKTO objective.

3.1 Targeted Token Weight Estimation

We first construct two contrastive language models, π^+ and π^-, to capture token-level preferences. Then, we use the log-ratio between these two models to estimate token-level importance weights.

KTO-based Contrastive LLM Construction. We propose a KTO-based approach to construct contrastive LLMs. KTO (Ethayarajh et al., 2024) uses unpaired data, enabling more flexible training. We build two contrastive LLMs, π^+ and π^-, where π^+ favors high- and π^- favors low-reward tokens. We train π^+ with normal labels and obtain π^- by simply flipping the labels, treating desirable as undesirable and vice versa.

Token-level Importance Sampling. We estimate the token's weight (Liu et al., 2025) as:

$$w_t = \exp(\mu \cdot \text{clamp}(\log \frac{\pi^+(y_t \mid x, y_{<t})}{\pi^-(y_t \mid x, y_{<t})}, L, U)), \tag{2}$$

where $\log \frac{\pi^+(y_t|x,y_{<t})}{\pi^-(y_t|x,y_{<t})}$ estimates the token's reward (Rafailov et al., 2024). We clamp this reward between L and U to enhance optimization stability. For desirable samples, we set $\mu > 0$; for undesirable ones, we set $\mu < 0$.

3.2 Token-level KTO

We extend KTO (Ethayarajh et al., 2024) to the *token level*, proposing Token-level KTO (TKTO) to learn finer-grained token-level signals.

Token-level Reward and Reference. We define the reward for each token y_t as its log-ratio against a reference policy π_{ref}:

$$r_{\theta,t}(x, y) = \log \frac{\pi_\theta(y_t \mid x, y_{<t})}{\pi_{\text{ref}}(y_t \mid x, y_{<t})}, \tag{3}$$

$$z_{0,t} = \text{KL}\Big(\pi_\theta(\cdot \mid x, y_{<t}) \,\Big\|\, \pi_{\text{ref}}(\cdot \mid x, y_{<t})\Big), \tag{4}$$

where $z_{0,t}$ is a fixed reference baseline estimated across a microbatch (no gradients propagated).

Model	PO Data	Female			Male		
		Acc ↑	CER ↓	Bad ↓	Acc ↑	CER ↓	Bad ↓
gpt-4o-mini-tts	-	0.900	0.109	0.079	0.939	0.111	0.062
gemini-2.5-flash-preview-tts	-	0.776	0.140	0.105	0.769	0.134	0.091
gemini-2.5-pro-preview-tts	-	0.871	0.127	0.094	0.885	0.119	0.073
F5-TTS (Chen et al., 2025)	-	0.498	0.173	0.189	0.500	0.177	0.183
F5-TTS with G2P (Oura et al., 2010)	-	0.500	0.136	0.100	0.500	0.146	0.107
Base model (Du et al., 2024)	-	0.683	0.128	0.090	0.668	0.138	0.095
Supervised Fine-Tuning (SFT)	Desirable	0.674	0.119	0.076	0.654	0.130	0.084
DPO (Tian et al., 2025)	Paired	0.706	0.120	0.076	0.693	0.130	0.082
KTO (Ethayarajh et al., 2024)	Paired	0.654	0.066	0.028	0.651	0.074	0.030
KTO (Ethayarajh et al., 2024)	Unpaired	0.933	0.079	0.030	0.952	0.087	0.032
TKTO (ours)	Paired	0.681	**0.059**	**0.025**	0.701	**0.066**	0.029
TKTO (ours)	Unpaired	**0.949**	0.075	0.029	**0.958**	0.085	**0.027**

Table 1: Accuracy (Acc), Character Error Rate (CER), and bad case ratio (Bad) across different models. The best and second-best results are highlighted in **bold** and underline, respectively.

Token-level Value Function. We define each token's value v_t using a logistic-shaped function:

$$v_t(x,y) = \begin{cases} \lambda_D\, \sigma\big(\beta\,(r_{\theta,t}(x,y) - z_{0,t})\big) \\ \qquad \text{if } y \sim y_{\text{desirable}} \mid x, \\ \lambda_U\, \sigma\big(\beta\,(z_{0,t} - r_{\theta,t}(x,y))\big) \\ \qquad \text{if } y \sim y_{\text{undesirable}} \mid x, \end{cases} \tag{5}$$

where $\sigma(\cdot)$ is the sigmoid function, β controls curvature, and λ_D, λ_U adjust aversion for desirable and undesirable samples.

Objective Function. The total TKTO loss is defined by summing token-level values across the sequence and weighting them by an importance weight w_t:

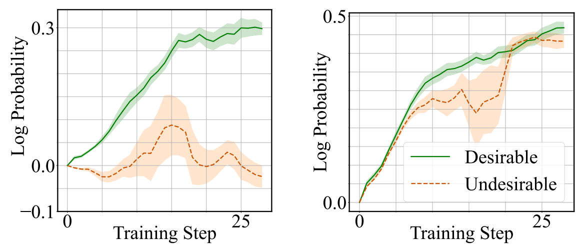
$$L_{\text{TKTO}} = \mathbb{E}_{(x,y)}\left[-\sum_{t=1}^{|y|} w_t \cdot v_t(x,y)\right]. \tag{6}$$

4 Experiments

4.1 Experimental Setup

Text Dataset. To evaluate not only CER but also more challenging cases of ambiguous Japanese pronunciation, we created a Japanese dataset of 5,000 sentences containing the word "辛い" using GPT-5 (OpenAI, 2025b). The word can be pronounced either as karai (spicy) or tsurai (hard), depending on the context; we ensured that each pronunciation appears in half of the samples.

Speech Dataset. For each text sentence, we generate five speech samples for both female and male Japanese speakers (Okamoto et al., 2023) using a



(a) TKTO (Ours) (b) SFT

Figure 3: Average log-likelihood for desirable and undesirable tokens during training. TKTO effectively increases only that of desirable tokens.

TTS model, with training data containing 23 hours of speech for each speaker. Among them, the sample with the correct pronunciation and the lowest CER is selected as a desirable sample. Conversely, the sample with the incorrect pronunciation and the highest CER is selected as an undesirable sample. The CER is computed using the whisper-v3-large (Radford et al., 2023).

Baselines. We use CosyVoice2 (0.5B) (Du et al., 2024) fine-tuned on 20K hours of Japanese speech data as our base model and apply our TKTO. The following baselines are considered:

- *Preference Optimization (PO) methods:* DPO uses 1.5K paired desirable–undesirable samples; KTO uses 9K unpaired desirable or undesirable samples; SFT uses 6K desirable samples.
- *TTS models:* Flow matching-based F5-TTS (Chen et al., 2025) trained on the 20K hours, w/ and w/o Japanese G2P (Oura et al., 2010).
- *Reference industry models:* gpt-4o-mini-tts (OpenAI, 2025a) (*Coral*: female, *Ash*: male) and

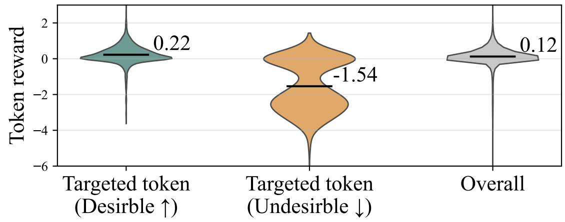


Figure 4: Token reward analysis. Desirable tokens have a higher reward, while undesirable tokens have a much lower reward, encouraging both weights to increase.

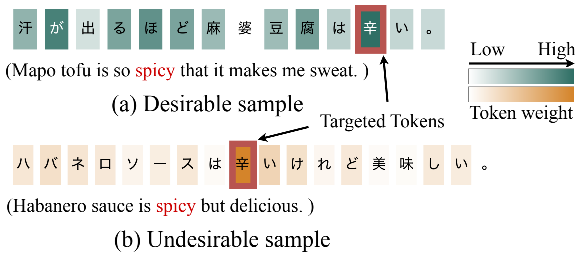


Figure 5: Case study of token weight estimation. The tokens of target character have higher weights.

gemini-2.5-tts-preview (Google, 2025) (*Zephyr*: female, *Puck*: male).

Objective Metrics: We use CER to evaluate overall robustness and the bad case ratio (Bad), where samples with CER exceed 0.3.

Subjective Metrics: We employ the naturalness mean opinion score (NMOS) to evaluate the naturalness. In addition, we conduct an ABX test. Please see Appendix A for more details.

4.2 Objective Evaluation Results

Main Results. Table 1 presents the objective evaluation results. Our TKTO model achieves the highest Japanese TTS accuracy and the lowest CER and bad case ratio. The non-LLM baseline F5-TTS shows extremely low accuracy regardless of whether it uses G2P or not, highlighting the importance of LLMs to consider contextual information. The use of unpaired data allows us to leverage samples that are always desirable or always undesirable, which cannot be used in paired training. This leads to a significant improvement in accuracy (0.949 or 0.958), surpassing even strong industry models. Using only paired data excludes samples that always produce desirable outputs, causing the model to overfit toward undesirable examples. As a result, accuracy improvement is limited, although the CER and bad case ratio become slightly lower. Compared with KTO, our model achieves improvements across all metrics, demonstrating the effectiveness of token-level targeted optimization.

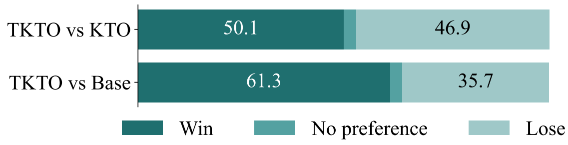


Figure 6: Results for ABX preference test.

	Base	KTO	TKTO (ours)
NMOS ↑	4.15	4.21	**4.26**

Table 2: NMOS comparison (higher is better).

Training Dynamics. Figure 3 illustrates the changes in the average log-likelihood of desirable and undesirable tokens. As training progresses, TKTO (left) effectively increases only that of desirable tokens, whereas SFT (right) tends to increase the log-likelihood of undesirable tokens.

Token Weight Analysis. Figure 4 illustrates the token rewards $\log \frac{\pi^+(y_t|x,y^{<t})}{\pi^-(y_t|x,y^{<t})}$ for desirable and undesirable tokens for the target character "辛" and the overall average. The desirable tokens have a higher reward (0.22) compared to the overall mean (0.12), while the undesirable tokens show a much lower value (-1.54), indicating that targeted tokens are automatically assigned larger weights. For undesirable samples, two peaks are observed when a clear difference between π^+ and π^- emerges; the reward drops sharply, whereas when no significant difference exists. Figure 5 also presents a case study showing that the tokens corresponding to the target characters receive notably higher weights.

4.3 Subjective Evaluation Results

Table 2 presents the NMOS subjective evaluation scores. Figure 6 shows the results of the ABX test. In the subjective evaluations, TKTO also outperforms the base model and the standard KTO.

5 Conclusion

We propose TKTO that eliminates the need for paired data, enabling a more data-efficient training paradigm, and directly targets token-level units, automatically providing fine-grained alignment signals without token-level annotations. TKTO serves as an off-policy approach compatible with human feedback, while extending it to an on-policy setting remains a promising direction for future work.

Limitations

The evaluations are conducted on only challenging Japanese data. Although multiple preference optimization methods and configurations were tested, the base model was limited to CosyVoice2 0.5B model due to the computational resources. While this work only focuses on preference optimization for TTS, the proposed TKTO framework can potentially be applied to other text generation tasks where specific tokens play a crucial role.

Ethical Considerations

While text-to-speech (TTS) technology may raise concerns regarding unauthorized generation or misuse, the models utilized in this paper were used for research purposes under controlled conditions.

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Parameter	Female			Male		
L, U	Acc ↑	CER ↓	Bad ↓	Acc ↑	CER ↓	Bad ↓
-1, 1	0.937	0.076	0.028	0.951	0.088	0.031
-2, 2	0.949	0.075	0.029	0.958	0.085	0.027
-3, 3	0.956	0.072	0.027	0.948	0.088	0.028

Table 3: Parameter sensitivity analysis.

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Appendix

A Subjective Evaluation Details

The instructions for the subjective evaluation are as follows. A Japanese native human annotator listened to the speech samples and rated their naturalness as NMOS on a 5-point scale, where 1 indicates very unnatural and 5 indicates completely natural. In addition, we conducted an ABX test in which the participant listened to two generated speech samples from different models but based on the same input and then chose the one that sounds more natural; if the samples are too similar to distinguish, they are instructed to indicate a tie. The annotator was recruited via a crowdsourcing platform and received appropriate compensation for their work.

B Implementation Details

Our implementation was based on the publicly available codes of prior work (Chen et al., 2025; Du et al., 2024), which are released under research-permissive licenses, and hyperparameters and libraries used followed those studies. Base model and baseline F5-TTS were initialized from the pre-trained checkpoints and fine-tuned once. Training took a few minutes on 8×A100 GPUs. All preference optimization experiments were conducted on 1 epoch with 1e-6 learning rate. We set $\lambda_D = \lambda_U = 1$, $\beta = 0.10$, we set $\mu = 1$ for desirable tokens, $\mu = -1$ for undesirable ones, following Ethayarajh et al. (2024).

C Parameter Sensitivity Analysis

Since the clamping range controls the scaling of the reward weights, it plays an important role in balancing learning stability and sensitivity. Table 3 presents the clamping range (L,U) sensitivity analysis results. While performance remains stable for moderate clamping ranges, wide bounds (e.g., (-3, 3)) can slightly lead to accuracy degradation. This suggests that imposing reasonable constraints on the reward range is beneficial for achieving optimal results. We select $(-2, 2)$ as the optimal range for experiments.