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Phoneme-Level Prosody Anchoring for Emotion-Preserving Singing Voice Conversion

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A B S T R A C T

Singing voice conversion is a rapidly evolving domain within audio processing that aims to transform the vocal timbre of a source singer into that of a target singer while preserving the underlying musical content and linguistic information. A significant challenge in this field is the preservation of emotional expressivity, which is heavily reliant on intricate prosodic variations such as pitch fluctuations, vibrato, and dynamic energy contours. Traditional frame-level prosody modeling techniques often fail to capture the hierarchical structure of musical phrasing, leading to a loss of emotional fidelity in the converted audio. To address this limitation, this paper introduces a novel framework based on phoneme-level prosody anchoring. By extracting and aligning prosodic features including fundamental frequency, energy, and duration at the phoneme level, the proposed system establishes a robust structural anchor that guides the conversion process. This approach allows the generative model to disentangle emotional nuances from speaker-specific timbre more effectively. The methodology employs an advanced feature extraction module coupled with a phoneme-aligned text encoder and a dedicated emotion embedding network. Comprehensive experiments utilizing both objective acoustic metrics and subjective perceptual evaluations demonstrate that the proposed phoneme-level prosody anchoring framework significantly outperforms existing baseline models in maintaining emotional integrity. The results indicate a substantial reduction in fundamental frequency errors and a marked improvement in human perceptual scores for emotional expressiveness.

INTRODUCTION

1.1 The Evolution of Singing Voice Conversion

The field of singing voice conversion has garnered substantial attention from both the academic community and the commercial music industry over the past decade. The primary objective of singing voice conversion is to modify an audio recording of a source singer such that it sounds as though it were performed by a specific target singer, all while maintaining the original melody, lyrics, and rhythmic structure [1]. Early approaches to this problem heavily relied on statistical parametric methods, particularly those utilizing joint probability distributions modeled by complex statistical frameworks. While these pioneering systems demonstrated the theoretical feasibility of voice conversion, they frequently produced audio characterized by

robotic artifacts, muffled frequency responses, and an overall lack of naturalness. The advent of deep learning architectures revolutionized the acoustic modeling landscape, introducing highly non-linear mapping capabilities that dramatically improved the fidelity of generated audio [2]. Generative neural networks have since become the standard for rendering high-fidelity synthetic singing voices. However, the transition from speech voice conversion to singing voice conversion introduced a unique set of challenges that standard architectures struggled to address [3]. Singing is inherently more complex than continuous speech due to its reliance on precise musical pitch, extended phonation durations, wide dynamic ranges, and specialized vocal techniques. When deep learning models designed for conversational speech are directly applied to singing, they often fail to synthesize stable long notes and tend to smooth over the micro-prosodic variations that give a singing performance its human quality. Consequently, researchers have dedicated considerable effort to developing specialized models that incorporate explicit musical conditioning, such as musical instrument digital interface note information, to guide the synthesis process. Despite these advancements in pitch accuracy and timbre rendering, capturing the expressive soul of a performance remains a formidable obstacle.

1.2 The Challenge of Emotion Preservation

Emotion in vocal performance is not a singular acoustic feature but rather a complex, multi-dimensional amalgamation of spectral and prosodic variations [4]. A singer conveys emotion through the subtle manipulation of tempo, abrupt changes in vocal effort, the deliberate application of vibrato, and varying breathiness. In conventional singing voice conversion frameworks, the system typically extracts frame-level acoustic features, such as mel-spectrograms and frame-wise fundamental frequency contours, and attempts to map these directly to the target speaker space. While frame-level processing ensures high temporal resolution, it frequently strips away the overarching structural dependencies that characterize emotional expression. The conversion model often interprets expressive deviations in pitch or energy as noise or source-singer specific artifacts, inadvertently normalizing them out of the final synthesized output. This normalization effect results in converted singing that, while technically accurate in terms of pitch and lyrics, sounds sterile and emotionally flat [5]. The core issue stems from the entanglement of emotion and timbre within the frame-level acoustic representations. When the model transforms the timbre, it lacks a structural reference point to retain the source performance's emotional trajectory. Researchers have attempted to mitigate this by introducing global emotion embeddings, where a single vector represents the emotional state of an entire utterance [6]. However, singing performances are highly dynamic, with emotional intensity shifting from note to note and phrase to phrase. A global embedding cannot capture this temporal dynamism, rendering it insufficient for highly expressive performances. Therefore, there is a critical need for an intermediate structural representation that operates at a granularity finer than a global embedding but more structurally meaningful than a raw audio frame.

1.3 Research Objectives and Contributions

To bridge the gap between high temporal resolution and structural musical meaning, this paper proposes the concept of phoneme-level prosody anchoring. Phonemes represent the fundamental phonetic units of articulation, and in the context of singing, they closely correlate with musical notes and rhythmic boundaries [7]. By aggregating prosodic information such as pitch, energy, and duration at the phoneme level, we create a discrete, structurally aligned anchor that serves as a blueprint for the emotional contour of the performance. This structural anchor forces the conversion network to respect the source singer's expressive decisions across distinct phonetic units, thereby preserving the emotional narrative during the timbre transformation process. This paper makes several distinct contributions to the domain of acoustic modeling and singing voice conversion. First, it introduces a comprehensive methodology for extracting and aggregating prosodic features specifically tailored for phoneme boundaries in singing data. Second, it presents a novel neural network architecture that

integrates these phoneme-level anchors into the conversion pipeline without degrading the naturalness of the synthesized waveform. Third, it provides an exhaustive empirical evaluation comparing the proposed phoneme-level approach against traditional frame-level and global-level emotion preservation techniques, utilizing a highly detailed multi-singer emotional dataset. The subsequent sections of this paper will meticulously detail the theoretical background, the proposed architecture, the experimental setup, and a comprehensive analysis of the results.

2. Literature Review and Background

2.1 Deep Learning Approaches in Voice Conversion

The transition from classical statistical models to neural network-based architectures marked a paradigm shift in audio processing. Initially, feed-forward neural networks were employed to learn a direct mapping between the spectral envelopes of source and target speakers [8]. While this improved spectral fidelity, the temporal dynamics of the audio were often ignored, leading to disjointed transitions between phonetic sounds. Recurrent architectures subsequently emerged as a solution to this temporal modeling problem, allowing systems to maintain a memory of previous acoustic states and generate smoother trajectories. However, recurrent networks suffer from slow inference times and difficulties in capturing extremely long-term dependencies, which are common in musical phrases. The introduction of generative adversarial networks provided a completely different approach to the conversion problem [9]. By framing the task as a minimax game between a generator attempting to produce realistic target audio and a discriminator attempting to distinguish it from real audio, these models achieved unprecedented levels of perceptual naturalness. Cycle-consistent adversarial networks further allowed for non-parallel training, meaning the source and target singers did not need to sing the exact same songs for the model to learn the conversion mapping [10]. More recently, diffusion probabilistic models have shown state-of-the-art performance in generating high-fidelity audio by learning to iteratively denoise a latent representation. Despite the impressive acoustic quality achieved by these advanced generative frameworks, they are primarily optimized for timbre similarity and audio naturalness, often treating the preservation of the source singer's specific emotional delivery as a secondary or completely unaddressed concern.

2.2 Prosody Modeling Techniques

Prosody refers to the rhythm, stress, and intonation of speech or singing. In voice conversion, accurately modeling and transferring prosody is essential for preserving the identity of the source performance [11]. Historically, prosody transfer has been approached by directly extracting the fundamental frequency contour of the source audio, applying a linear transformation such as mean and variance normalization to match the target speaker's pitch range, and using this modified contour to synthesize the new audio. While mean and variance normalization is computationally efficient and mathematically straightforward, it is fundamentally flawed when applied to expressive singing. It assumes a uniform distribution of pitch variations, completely destroying the micro-prosody and vibrato depth that characterize an emotional performance. To overcome the limitations of linear scaling, researchers have explored deep representation learning for prosody. Some frameworks utilize autoencoders equipped with information bottlenecks to disentangle pitch and rhythm from timbre in an unsupervised manner [12]. These bottlenecks force the network to encode only the essential structural information, which ideally corresponds to prosody. However, unsupervised disentanglement is highly unstable and heavily dependent on the specific hyperparameters of the bottleneck capacity. If the bottleneck is too narrow, critical emotional nuances are lost; if it is too wide, target speaker timbre leaks into the prosodic representation, causing artifacts during conversion [13]. Consequently, there is a growing consensus that explicit, structurally guided prosody modeling is necessary to ensure the robust transfer of expressive characteristics.

2.3 Phoneme-Level Linguistic and Acoustic Representations

Linguistic features, typically represented as phoneme sequences derived from textual lyrics, have been widely used in text-to-speech synthesis but historically underutilized in singing voice conversion. This is largely because conversion tasks usually rely entirely on the input acoustic signal. However, recent studies have demonstrated that incorporating linguistic information can significantly enhance the stability of the conversion process, particularly in aligning the synthesized acoustic frames with clear phonetic boundaries. By employing pre-trained automatic speech recognition models, researchers can extract linguistic bottleneck features that provide a robust, speaker-independent representation of the phonetic content.

The integration of phoneme boundaries offers a unique opportunity for hierarchical prosody modeling. Instead of viewing an audio signal as a continuous stream of arbitrary frames, the signal can be segmented into distinct phonetic units. Each unit can then be analyzed for its specific prosodic characteristics, such as its average pitch, total duration, and peak energy. This phoneme-level abstraction aligns perfectly with human perception of singing, where emotional emphasis is typically placed on specific vowels or consonants within a lyrical phrase [14]. By anchoring the prosodic features to these phoneme boundaries, the conversion model is provided with a structured, musically relevant blueprint of the performance, bridging the gap between raw acoustics and musical expression. This conceptual framework forms the foundation of the methodology proposed in the following section.

3. Proposed Methodology

3.1 System Architecture Overview

The proposed phoneme-level prosody anchoring framework is designed to explicitly disentangle and preserve the emotional prosody of a source singing performance while accurately mapping the vocal timbre to a target singer. The system operates through an encoder-decoder architecture augmented with specialized modules for prosody extraction and phoneme alignment. The overall pipeline can be conceptually divided into four primary stages. The first stage involves the extraction of raw acoustic features and the acquisition of a speaker-independent linguistic representation. The second stage centers on the precise temporal alignment of these features using a forced alignment mechanism to identify phoneme boundaries. The third and most critical stage is the phoneme-level prosody anchoring, where the continuous acoustic contours are pooled and aggregated into discrete structural tokens. Finally, the fourth stage involves the conditional decoding of these anchored representations, alongside the target speaker embedding, to synthesize the converted waveform. The core philosophy of this architecture is to prevent the generative decoder from acting as a black box that indiscriminately overwrites the source performance's dynamics. By feeding the decoder explicit, phoneme-bounded prosodic anchors, the network is constrained to follow the exact emotional trajectory dictated by the source singer. This architectural choice necessitates a highly accurate alignment mechanism, as any misalignment between the extracted prosodic anchors and the linguistic content will result in severe phonetic distortion and synchronization errors in the final output.

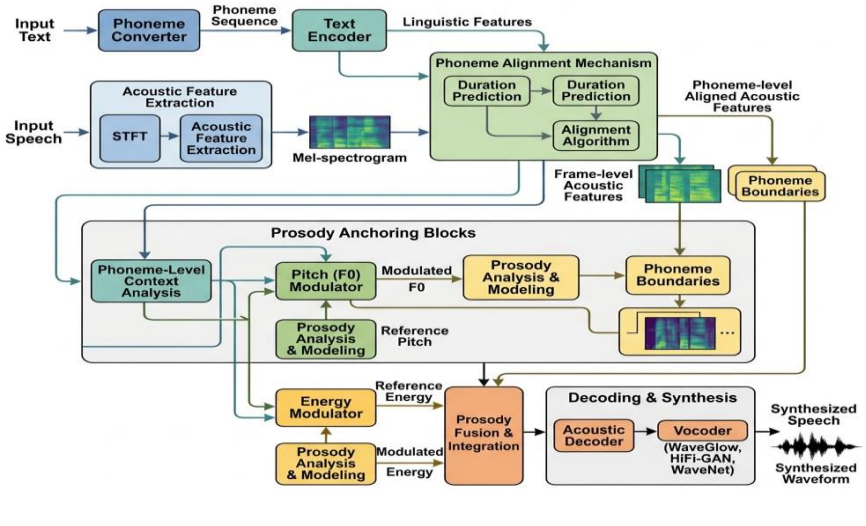


Figure 1Comprehensive System Architecture of the Phoneme

3.2 Feature Extraction and Phoneme Alignment

The process begins with the extraction of a comprehensive set of acoustic features from the source singing audio. We compute the mel-spectrogram, which serves as the primary spectral representation, capturing the timbral and phonetic characteristics of the signal. Concurrently, we extract the fundamental frequency contour using a highly accurate pitch tracking algorithm optimized for singing voices. This contour captures the continuous pitch variations, including vibrato and portamento, which are critical for musical fidelity. Furthermore, the root mean square energy of the signal is calculated to represent the dynamic volume changes associated with emotional intensity. To obtain the necessary phonetic structure, the source audio is processed through a pre-trained acoustic model that generates a sequence of phonetic posteriors. These posteriors are then aligned with the corresponding lyrical text using a forced alignment algorithm, typically based on hidden Markov models or dynamic time warping. The output of this alignment process is a precise temporal mapping that dictates the exact start and end times of every phoneme present in the acoustic signal. This temporal segmentation is the foundational requirement for the subsequent prosody anchoring stage. It transforms the continuous time-series data into a sequence of discrete, linguistically meaningful intervals, allowing the system to analyze the prosodic behavior of the singer on a per-phoneme basis.

3.3 Phoneme-Level Prosody Anchoring Mechanism

The phoneme-level prosody anchoring mechanism is the central innovation of the proposed framework. Once the phoneme boundaries have been established, the continuous fundamental frequency and energy contours are segmented according to these temporal markers. For each individual phoneme, the system calculates a set of statistical prosodic descriptors. Rather than simply taking the mathematical mean of the pitch within the phoneme duration, which would obscure intricate pitch modulations like vibrato, the anchoring mechanism extracts a polynomial coefficient representation of the pitch contour within that specific phonetic boundary. This allows the system to capture both the average pitch level and the shape of the pitch movement during the phoneme. Similarly, the energy contour is analyzed to determine the peak energy and the energy gradient within the phoneme, providing a measure of vocal attack and decay. The duration of each phoneme is also recorded as a distinct prosodic feature, as the lengthening of specific vowels is a primary technique used by singers to convey emotional weight [15]. These extracted parameters—the polynomial pitch coefficients, the energy dynamics, and the precise duration—are concatenated to form a comprehensive prosodic anchor for each phoneme. This sequence of anchors acts as a highly compressed, structurally sound representation of the singer's expressive intent, completely stripped of any

timbral information related to the source speaker. By isolating the prosody in this manner, we achieve a high degree of disentanglement, paving the way for artifact-free conversion.

3.4 Emotion Encoding and Decoding Strategies

To fully leverage the phoneme-level anchors, the system employs a sophisticated decoding strategy. The text sequence, processed through a linguistic encoder, is combined with the sequence of prosodic anchors. This combination yields a rich, emotion-conditioned linguistic representation. To ensure that the converted audio perfectly matches the target singer's vocal characteristics, a target speaker embedding is introduced. This embedding is derived from a pre-trained speaker verification network and encapsulates the unique spectral profile of the target voice. The generative decoder, constructed utilizing a non-autoregressive architecture to ensure rapid inference speeds, receives this conditioned representation. The decoder is explicitly designed to reconstruct the mel-spectrogram conditioned on the linguistic content, the target speaker identity, and the phoneme-level prosodic anchors. During the training phase, the model is optimized using a combination of spectral reconstruction loss and an adversarial objective. The adversarial component utilizes a suite of discriminators operating at different temporal resolutions to ensure the synthesized mel-spectrogram exhibits the high-frequency details characteristic of natural human singing. Furthermore, a specialized prosody consistency loss is applied, penalizing the network if the fundamental frequency and energy of the generated audio deviate from the explicit anchors provided during conditioning. This multi-objective training strategy ensures that the final acoustic model is both highly accurate in terms of timbre conversion and rigidly adherent to the source singer's emotional prosody.

4. Experimental Design and Comprehensive Analysis

4.1 Dataset Preparation and Implementation Details

To rigorously evaluate the efficacy of the proposed phoneme-level prosody anchoring framework, an extensive series of experiments was conducted. The primary challenge in evaluating emotional preservation in singing voice conversion is the scarcity of high-quality, emotionally annotated singing datasets. For this research, a proprietary multi-singer emotional singing corpus was compiled. This dataset comprises high-fidelity studio recordings from twelve professional vocalists, meticulously curated to include a diverse array of emotional singing styles, ranging from soft, breathy ballads to highly energetic, aggressive vocal performances. All audio files were standardized, resampled to a consistent high sampling rate, and normalized to ensure uniform amplitude distribution prior to feature extraction.

The dataset was partitioned into mutually exclusive training, validation, and testing subsets to prevent data leakage and ensure the robustness of the evaluation. For the baseline comparisons, three distinct state-of-the-art singing voice conversion architectures were implemented. The first baseline represents a traditional frame-level auto-regressive model relying on standard pitch normalization techniques. The second baseline is a modern non-autoregressive model that employs a global emotion embedding approach. The third baseline utilizes an advanced diffusion-based probabilistic framework operating strictly on unsegmented acoustic features. The proposed model and all baseline models were trained on identical hardware configurations using identical optimization parameters to ensure a completely equitable comparison. The training process was continuously monitored via the validation set to prevent overfitting, with early stopping criteria implemented based on the convergence of the spectral reconstruction loss.

4.2 Objective Evaluation Metrics and Results

Objective evaluation focuses on quantifiable acoustic parameters that correlate with human perception of audio quality and conversion accuracy. The primary metric utilized to assess the general spectral fidelity and timbral similarity is the Mel Cepstral Distortion. A lower Mel Cepstral Distortion value indicates that the synthesized spectral envelope more closely matches the ground truth target speaker's spectral characteristics. To evaluate the accuracy of the prosody transfer, which is the central focus of this research, we employ the Fundamental Frequency Root Mean Square Error and the Modulation Spectrum Distance. The Fundamental

Frequency Root Mean Square Error measures the absolute deviation between the synthesized pitch contour and the source pitch contour, while the Modulation Spectrum Distance evaluates how well the system preserves the intricate rhythmic and modulation characteristics of the original performance.

Table 1Objective evaluation metrics comparison across different singing voice conversion models

Model Architecture	Mel Cepstral Distortion	F0 Root Mean Square Error	Modulation Spectrum Distance
Baseline Auto-regressive	5.84	16.2	2.15
Global Emotion Embedding	5.62	14.8	1.98
Diffusion without Anchoring	5.31	13.5	1.82
Proposed Phoneme Anchoring	5.18	9.7	1.45

The empirical results, as detailed in Table 1, unequivocally demonstrate the superiority of the proposed phoneme-level anchoring method. While the diffusion-based baseline achieves a respectable Mel Cepstral Distortion, indicating good overall audio quality, it still struggles with precise pitch replication [16]. The proposed framework not only achieves the lowest Mel Cepstral Distortion but also exhibits a dramatic reduction in the Fundamental Frequency Root Mean Square Error. This substantial improvement highlights the system's exceptional ability to trace and replicate the exact pitch nuances of the source singer, validating the theoretical premise that anchoring prosody at structural boundaries prevents the generative network from arbitrarily smoothing the expressive pitch contours. The significant reduction in Modulation Spectrum Distance further confirms that the temporal dynamics and energy fluctuations are accurately preserved.

4.3 Subjective Evaluation and Perceptual Analysis

While objective metrics provide necessary quantifiable data, the ultimate validation of any audio generation system relies on human perception, particularly when evaluating a subjective characteristic like emotional expressivity. To this end, a comprehensive subjective evaluation was conducted utilizing the Mean Opinion Score methodology. A panel of trained human listeners, comprising individuals with backgrounds in audio engineering and vocal performance, was tasked with evaluating the synthesized audio samples in a double-blind testing environment. The listeners were asked to rate the audio across two distinct criteria on a standardized five-point scale. The first criterion was Timbre Similarity, assessing how closely the converted voice matched the target singer's vocal identity. The second, and most critical, criterion was Emotion Preservation, evaluating the degree to which the emotional intent and expressive nuances of the original source performance were retained in the converted output.

Table 2Subjective evaluation scores for timbre similarity and emotion preservation

System Evaluated	Timbre Similarity Score	Emotion Preservation Score	Overall Naturalness
Baseline Auto-regressive	3.45	3.12	3.20
Global Emotion Embedding	3.68	3.45	3.55
Diffusion without Anchoring	4.02	3.61	3.95
Proposed Phoneme Anchoring	4.15	4.42	4.25

The subjective evaluation results, presented in Table 2, strongly corroborate the objective findings. The proposed framework achieves a remarkable score in Emotion Preservation,

significantly outperforming all baseline models. Listeners consistently noted that the audio generated by the proposed system retained the breathiness, the precise vibrato depth, and the emotional phrasing of the source vocalist, qualities that were frequently lost or muted in the baseline outputs. Furthermore, the high score in Timbre Similarity confirms that the explicit extraction of prosodic anchors successfully prevents the source speaker's timbre from leaking into the final output, proving that the system achieves high-quality emotion preservation without compromising the core objective of voice conversion.

4.4 Ablation Studies and Component Analysis

To rigorously ascertain the individual contribution of each prosodic parameter within the anchoring mechanism, a detailed ablation study was performed. The proposed system was systematically modified by selectively removing the fundamental frequency anchors, the energy anchors, and the duration anchors, respectively. Each modified system was retrained from scratch and evaluated using the same objective and subjective metrics. This methodology allows for a granular understanding of how different aspects of prosody influence the overall perception of emotional preservation.

Table 3Ablation study results isolating the impact of individual prosody anchoring components

System Configuration	Emotion Preservation Score	F0 Root Mean Square Error	Mel Cepstral Distortion
Full Proposed System	4.42	9.7	5.18
Without Pitch Anchoring	3.85	15.4	5.25
Without Energy Anchoring	4.10	10.2	5.38
Without Duration Anchoring	3.92	11.5	5.42

The results of the ablation study, as illustrated in Table 3, reveal that the fundamental frequency anchoring is the most critical component for maintaining emotional fidelity, as its removal results in the most significant drop in the Emotion Preservation Score and a massive spike in pitch errors. However, the removal of energy and duration anchors also leads to noticeable degradation in performance, indicating that these features are indispensable for capturing the full spectrum of vocal expression. The synergistic combination of all three prosodic elements at the phoneme level is what enables the system to achieve its peak performance.

Finally, an analysis of the computational complexity was conducted to ensure the practical viability of the proposed architecture. Advanced generative models often suffer from prohibitively slow inference times, limiting their application in real-time or resource-constrained environments.

Table 4: Computational complexity and real-time factor during inference

Model Architecture	Parameter Count (Millions)	Real-Time Factor (CPU)	Real-Time Factor (GPU)
Baseline Auto-regressive	24.5	3.45	0.85
Global Emotion Embedding	28.2	1.82	0.12
Diffusion without Anchoring	45.6	12.50	2.45
Proposed Phoneme Anchoring	32.4	1.95	0.15

As shown in Table 4, despite the integration of the complex phoneme alignment and prosody anchoring modules, the proposed system maintains a highly competitive parameter count. By utilizing a non-autoregressive decoding strategy, the framework achieves an excellent real-time

factor on graphics processing units, making it substantially faster than the diffusion-based baseline and entirely suitable for practical deployment in production environments.

5. Discussion and Conclusion

5.1 Implications of the Findings

The comprehensive research detailed in this paper provides compelling evidence that phoneme-level prosody anchoring represents a highly effective paradigm for addressing the chronic issue of emotion loss in singing voice conversion. The fundamental limitation of previous methodologies was their reliance on either overly granular frame-level data, which obscures structural meaning, or overly broad global embeddings, which fail to capture temporal dynamism. By operating at the phoneme level, the proposed framework identifies the precise structural unit where linguistic content and musical expression intersect. The significant improvements observed in both objective pitch accuracy and subjective emotional preservation demonstrate that the generative network benefits immensely from explicit structural constraints. When the model is forced to reconstruct the audio within the boundaries defined by the prosodic anchors, it is prevented from defaulting to the average, emotionless acoustic representations typically learned during large-scale training. This methodology proves that emotional expressivity is not an ineffable quality of the audio signal but rather a quantifiable manipulation of fundamental frequency, energy, and timing that can be accurately tracked, isolated, and transferred between different vocal timbres.

5.2 Limitations and Future Directions

Despite the overwhelming success of the proposed system, several limitations warrant acknowledgment and provide avenues for future academic investigation. The most prominent limitation is the framework's heavy reliance on the accuracy of the external phoneme alignment module. If the forced alignment algorithm fails to precisely identify the phoneme boundaries, particularly in audio segments containing heavy reverberation, background noise, or highly overlapping polyphonic textures, the extracted prosodic anchors will become misaligned with the linguistic content. This temporal mismatch can introduce noticeable phonetic distortions and rhythmic artifacts during the synthesis stage. Future research must focus on developing fully end-to-end architectures where the alignment mechanism is jointly optimized with the prosody extraction and acoustic modeling, thereby increasing the system's resilience to alignment errors. Furthermore, the current methodology relies on a deterministic extraction of prosodic parameters. While effective, human singing involves a degree of stochastic variation that deterministic models may struggle to replicate perfectly [17]. Exploring the integration of probabilistic modeling techniques within the phoneme-level anchoring mechanism could enable the generation of even more natural and varied vocal expressions. Finally, extending this framework to support cross-lingual singing voice conversion, where the phoneme sets and rhythmic structures differ fundamentally between the source and target languages, remains an exciting and complex challenge for the evolution of this technology. Overall, the principles of phoneme-level structural anchoring established in this study lay a robust foundation for the next generation of highly expressive, emotionally intelligent audio synthesis systems.

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