Reinforcement Learning for Personalized Text-to-Speech (TTS) Emotion Adaptation

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***Abstract*—Expressive and emotionally resonant Text-to-Speech (TTS) systems are critical for enhancing human-computer interaction. However, contemporary TTS models often struggle to move beyond generic emotional expressions, lacking the ability to generate speech that is personalized or adapted to specific prosodic targets. This paper introduces a novel framework for personalized emotion adaptation in end-to-end TTS. We propose fine-tuning a pre-trained Tacotron 2 model using a deep reinforcement learning agent based on Proximal Policy Optimization (PPO). The agent learns a policy to dynamically modify synthesized speech to match the prosodic characteristics of a target emotional utterance. Our reward function is explicitly designed to minimize the distance between the acoustic features—such as pitch, energy, and duration—of the generated and target speech. Through both objective and subjective evaluations on standard emotional speech datasets, we demonstrate that our PPO-based approach significantly improves the model's ability to control emotional expression compared to the baseline Tacotron 2. This work presents a viable and effective method for creating more adaptive and personalized speech synthesis systems.**

***Index Terms*—Speech Emotion Recognition, Reinforcement Learning, Deep Q-Network, Policy Gradient, Actor-Critic, Expressive Speech, Emotional Adaptation, End-to-End Speech Systems.**

I. Introduction

In the last decade, voice-based human-computer interaction has become ubiquitous, with applications ranging from smart home assistants and in-car navigation systems to accessibility tools for the visually impaired. This proliferation has been driven by significant advancements in Text-to-Speech (TTS) technology. The field has largely transitioned from older, more robotic-sounding concatenative and parametric methods to end-to-end neural models that can generate highly natural and intelligible speech directly from text [9]. Architectures like Tacotron 2, which combine recurrent neural networks with attention mechanisms, represent the state-of-the-art, effectively eliminating the complex multi-stage pipelines of their predecessors and producing speech that is often indistinguishable from human recordings [11].

However, as the naturalness of synthesized speech approaches human levels, the next frontier has become expressiveness and affective control. While state-of-the-art models can be trained to produce speech with general emotional tones (e.g., happy, sad, angry), the methods for achieving this control have notable limitations. Techniques often rely on learning a fixed set of style embeddings from the training data, using methods like Global Style Tokens (GSTs) or Variational Autoencoders (VAEs) [2]. These approaches are effective at capturing the dominant emotional styles present in a corpus, but they inherently provide a "one-size-fits-all" solution. They struggle to generate nuanced emotional expressions that lie between the learned styles and, more importantly, they lack a direct mechanism for personalizing speech or adapting it to match an external acoustic target on the fly. This inflexibility represents a critical gap, preventing the development of truly empathetic systems that can adapt their vocal prosody to a user's emotional state or a specific conversational context.

To bridge this gap, we reconceptualize the task of emotion adaptation as a sequential decision-making problem, making it ideally suited for a Reinforcement Learning (RL) framework. In this paper, we propose a novel method that leverages deep RL to perform fine-grained, personalized emotion adaptation in TTS. Our approach employs a pre-trained Tacotron 2 model as the synthesis backbone and introduces a lightweight RL agent, guided by the Proximal Policy Optimization (PPO) algorithm [7], to fine-tune its output. We chose PPO for its data efficiency and stable training dynamics, which are crucial for preventing catastrophic forgetting or degradation of the highly-performant base TTS model. The agent learns an optimal policy to adjust the prosodic characteristics of the synthesized speech—specifically its pitch, energy, and duration—to iteratively match those of a target emotional utterance. This is achieved through a carefully designed reward function that quantifies the prosodic similarity between the generated and target audio samples. The successful application of RL in adjacent fields like automatic speech recognition further validates its potential for complex speech manipulation tasks [13], [14].

The primary contributions of this work are three-fold:

- We introduce a novel framework that integrates a PPO-based reinforcement learning agent with a Tacotron 2 TTS model for the specific task of personalized emotion adaptation.
- We design and implement a dedicated prosody-based reward function that effectively guides the synthesis process towards a target emotional style by minimizing the distance between key acoustic features.
- We provide a comprehensive evaluation using both objective metrics and subjective listening tests on standard emotional speech datasets, demonstrating our method's significant improvement in generating emotionally adaptive speech over a baseline Tacotron 2 model.

The remainder of this paper is organized as follows. Section II reviews related work in expressive TTS and reinforcement learning. Section III details our proposed methodology. Section IV describes the experimental setup and evaluation metrics. Section V presents and discusses our results, and Section VI concludes the paper with directions for future work.

II. Related Works

Our research is situated at the intersection of three key domains: end-to-end Text-to-Speech (TTS) synthesis, expressive prosody control, and the application of Reinforcement Learning (RL) to speech processing. This section presents a critical review of foundational and contemporary works in these areas. We begin by charting the evolution of TTS technology to establish the importance of modern end-to-end models. We then delve into the specific challenges of emotion and prosody control, highlighting the limitations of existing techniques. Finally, we provide a detailed analysis of how Reinforcement Learning has been applied to speech processing, building a clear and compelling case for our proposed methodology.

A. The Evolution to End-to-End Text-to-Speech Synthesis

The pursuit of synthetic speech that is indistinguishable from human voice has a long history, marked by several paradigm shifts. Early systems relied on concatenative synthesis, which involved stitching together pre-recorded units of speech (like diphones or phonemes). While this could produce natural-sounding segments, the results were often plagued by audible artifacts at the concatenation points and lacked prosodic coherence. The subsequent move to statistical parametric speech synthesis (SPSS), using technologies like Hidden Markov Models (HMMs), offered smoother and more consistent prosody but often suffered from a "buzzy" or "muffled" quality due to the over-smoothing of acoustic features.

The advent of deep learning instigated a revolution in the field, leading to the development of end-to-end neural TTS models. These models cast the entire process of converting text to speech as a single mapping learned by a deep neural network, eliminating the need for complex, multi-stage feature engineering pipelines. A landmark achievement in this area is Tacotron 2 [11], an architecture that combines a recurrent sequence-to-sequence model with an attention mechanism. Its encoder, typically a stack of convolutional and recurrent layers, processes the input text to produce a robust hidden representation. The location-sensitive attention mechanism then aligns this text representation with the acoustic frames of the output spectrogram, allowing the model to learn a stable and monotonic alignment between text and speech. Finally, a decoder network generates a mel-spectrogram, which is converted into an audible waveform by a neural vocoder like WaveNet or, more recently, HiFi-GAN. The success of this architecture has been replicated across numerous languages, including a high-quality Turkish TTS system that achieved a Mean Opinion Score (MOS) of 4.49 by pairing Tacotron 2 with a HiFi-GAN vocoder [10].

While models like Tacotron 2 represent a pinnacle of naturalness in neutral speech, their very structure, designed for stability and consistency, makes fine-grained expressive control a non-trivial challenge. Our work leverages the proven quality of the Tacotron 2 architecture as a stable foundation, focusing not on redesigning the core synthesis process but on building a sophisticated control layer on top of it.

B. The Challenge of Prosody and Emotion Control in TTS

As the baseline quality of TTS has improved, research focus has shifted to controlling the expressive aspects of speech—the rhythm, pitch, and intonation collectively known as prosody. Initial attempts at emotion control relied on supervised learning with explicit emotion labels (e.g., "happy," "sad"). However, this approach is limited by the subjective and discrete nature of such labels and fails to capture the vast, continuous spectrum of human emotion.

To overcome this, unsupervised methods were developed to learn "styles" directly from data without explicit labels. Techniques like Global Style Tokens (GSTs) learn a fixed-size dictionary of style embeddings from the training data. During synthesis, a specific style can be invoked by selecting one of these tokens. Similarly, Variational Autoencoders (VAEs) can be used to learn a continuous latent space of prosodic styles. While powerful, these methods share a fundamental limitation: they are designed to model the distribution of styles present in the training data. They provide no direct mechanism for adapting to a novel target prosody that was not seen during training or for personalizing the output to a specific user's vocal characteristics.

This limitation is a critical barrier to creating truly interactive and empathetic systems. The related field of Speech Emotion Recognition (SER) offers valuable insights into the acoustic features that correlate with emotion. For instance, research has shown that hierarchical

modeling can improve SER accuracy by capturing different levels of acoustic detail [3]. However, recognition is a distinct and arguably simpler task than generation. Our work addresses the generation problem head-on, framing prosody adaptation not as a classification task, but as a dynamic, target-matching problem.

C. Reinforcement Learning as a Framework for Speech Control

Reinforcement Learning offers a compelling framework for sequential decision-making problems, particularly those where a direct, differentiable objective function is unavailable. This makes it exceptionally well-suited for fine-grained control tasks in speech processing. A detailed comparison of the key RL-based speech processing works is presented in Table II.

1) Foundational Applications of RL in Automatic Speech Recognition (ASR): Much of the pioneering work applying RL to speech processing occurred in the domain of ASR. A primary motivation was to overcome the discrepancy between the training objectives of traditional sequence-to-sequence models and the ultimate evaluation metrics. Models trained with frame-level losses (like cross-entropy) were not being optimized directly for sequence-level metrics like Word Error Rate (WER). RL, through policy gradient methods, provided a solution by allowing the model to be fine-tuned using a reward signal based directly on the desired metric (e.g., a negative WER) [11]. This approach also helped mitigate the problem of exposure bias, where a model trained only on ground-truth inputs falters when faced with its own, potentially imperfect, predictions during inference. RL allows the model to explore its own prediction space and learn to recover from errors.

Further research in ASR has demonstrated the versatility of RL. It has been used to incorporate implicit user feedback (e.g., from an N-best list) in a semi-supervised manner [12] and, more recently, to fine-tune powerful pre-trained models like wav2vec2 with PPO, achieving significant further reductions in WER [14]. The consistent success of RL in fine-tuning strong supervised baselines in ASR provides a powerful precedent for applying the same principle to the generative task of TTS.

2) The Emergence of RL for Expressive Speech Synthesis: More recently, RL has been applied directly to the problem of expressive TTS, aiming to give users dynamic control over the generated speech. The central idea, as surveyed in Table III, is to use an RL agent to iteratively refine the output of a TTS model.

Several strategies for the reward signal have been explored. One approach is to use human-in-the-loop feedback, where a user's subjective rating (e.g., a Mean Opinion Score) is used as the reward. For example, researchers have wrapped a PPO feedback loop around Tacotron 2, using MOS scores to guide the agent in modifying prosodic features like pitch and speed [3]. While this directly optimizes for human preference, it is extremely costly, slow, and suffers from the inherent subjectivity and inconsistency of human raters, making it impractical for large-scale training.

Another approach uses proxy metrics derived from auxiliary models. For instance, some have combined transformers with Deep Q-Learning (DQN) and used the confidence score from an emotion classifier as the reward signal [4]. The agent is rewarded for producing audio that the classifier identifies as the target emotion. This is more scalable than human feedback, but it introduces a new dependency: the performance of the entire system is now capped by the accuracy of the auxiliary classifier. Furthermore, it optimizes for a categorical label, not for the specific acoustic nuances of a target utterance.

Our work is situated within this research thrust but addresses a key limitation of prior methods. We argue that for true personalization—matching the prosody of a specific target utterance—the reward function must be grounded in objective, measurable acoustic features, a point we elaborate on below.

3) Justification for an Objective, Acoustic-Based Reward Function: The limitations of existing RL-based TTS control methods—the high cost of human feedback and the indirectness of proxy metrics—motivate our core contribution. We propose that a more direct, consistent, and scalable approach is to define the reward function based on the acoustic similarity between the generated audio and the target audio. By selecting key prosodic features that are well-established correlates of emotion—namely pitch contour, energy, and phoneme duration—we can formulate a reward signal that is both objective and directly relevant to the task of emotion adaptation.

This approach offers several distinct advantages: 1. Objectivity and Consistency: The reward is calculated algorithmically, removing the subjectivity and noise associated with human raters. 2. Scalability: It requires no manual labeling or feedback, allowing the agent to be trained on vast amounts of data automatically. 3. Fine-Grained Control: By optimizing for similarity across multiple acoustic dimensions, the agent can learn to reproduce subtle prosodic nuances rather than just a broad emotional category.

By framing the problem in this way, our work aligns closely with the goals of personalized TTS while proposing a more practical and robust methodology for achieving it. The following section details the specific architecture and the mathematical formulation of our proposed PPO-based framework.

III. Taxonomy of Reinforcement Learning in Speech Processing

To systematically understand the diverse landscape of Reinforcement Learning applications in speech processing, we introduce a taxonomy that classifies the surveyed methods based on their underlying algorithmic principles. The field has seen a variety of approaches, each with distinct

TABLE I: Emotional Adaptation Target Aspects Investigated Across Surveyed Models

Aspect Targeted	**Description**	**Referenced In**
Prosody Control	Adjusting fundamental acoustic features like pitch, duration, and stress to align with a desired emotion.	[1], [3], [5], [10]
Expressiveness Tuning	Modulating the overall intensity or level of expressiveness in the synthesized speech output.	[1], [2], [4], [6], [7]
User Personalization	Learning from feedback to adapt the speech style to a specific user's emotional preferences or vocal characteristics.	[1], [3], [5], [9]
Noise Robustness	Improving the accuracy of emotion recognition or the clarity of emotional synthesis in noisy acoustic conditions.	[8]
Cross-Domain Transfer	Generalizing a learned emotional adaptation model to unseen emotion types, speakers, or datasets.	[9], [10]

TABLE II: Comparative Analysis of Foundational and Contemporary Works in Reinforcement Learning for Speech Processing

Reference	**Year**	**Primary Objective**	**Key Contribution & Method (Merit)**	**Identified Limitations or Trade-offs (Demerit)**
[11]	2017	Optimize ASR models for sequence-level metrics using RL.	Pioneered Policy Gradient for ASR. Used negative Levenshtein distance to minimize WER.	Unstable training; relies on pre-trained models.
[12]	2017	Enable semi-supervised RL updates for ASR with user feedback.	Introduced lightweight user feedback. Used N-best list selection as reward.	Proxy reward less precise than WER optimization.
[8]	2020	Enhance seq2seq models by mitigating exposure bias.	Applied PG, A2C, DQN to seq2seq. Aligned training with metrics like ROUGE.	Computationally expensive; convergence instability.
[13]	2020	Improve time-efficiency of ASR training with deep RL.	Showed pre-training accelerates and stabilizes RL.	Dependent on strong supervised baselines.
[3]	2021	Improve SER with audio and text modalities.	Developed hierarchical DNN with ELMo embeddings. Achieved 81%+ accuracy.	Relies on handcrafted features; high complexity.
[9]	2021	Assess controllability of expressive TTS system.	Mapped expressiveness to latent space using DCTTS.	Requires significant data; limited interpretability.
[5]	2022	Improve SER with Zeta Policy and pre-training.	Introduced Zeta Policy in DQN for reward stability.	Lags behind supervised models; requires 700k steps.
[1]	2023	Develop speech recognition for Nigerian languages.	Combined DRL, HMM, LSTM for 96.62% accuracy.	High complexity; narrow isolated-word focus.
[7]	2023	Improve dialogue policy with audio embeddings.	Fused Wav2Vec2, HuBERT with Actor-Critic RL.	Less benefit than supervised; high cost.
[14]	2023	Build end-to-end ASR system with RL.	Integrated PPO with wav2vec2 for 4% WER improvement.	Incremental gains; needs strong base model.
[4]	2025	Develop personalized speech therapy with RL.	Integrated PPO with LLMs for 97.9% accuracy.	High demands; potential real-time latency.

mechanisms for learning and optimization. Our classification, visualized in Figure 1, organizes these techniques into three primary categories: value-based, policy-based, and hybrid methods, which often combine elements of the first two. This structured overview helps to contextualize the various contributions in the literature and highlight the prevailing trends and trade-offs.

A. Value-Based Methods

Value-based reinforcement learning methods are centered on learning a value function that estimates the expected return (cumulative future reward) of being in a particular state or taking a specific action in a state. The optimal policy is then derived implicitly by selecting the action that leads to the state with the highest value. The most prominent algorithm in this category is Deep Q-Learning (DQN) and its variants. In the context of speech, a DQN agent learns to predict the long-term emotional impact or acoustic quality of a particular synthesis choice. As shown in our survey (Table V), DQN has been widely applied for its conceptual simplicity and effectiveness in discrete action spaces. For example, it has been used to fine-tune emotional tone by treating different style vectors as actions [4] and to learn optimal policies for speech emotion recognition [2], [5]. The key components of these methods often include a target network for stabilizing training and techniques like reward shaping to guide the agent more effectively.

B. Policy-Based Methods

In contrast to value-based approaches, policy-based methods directly learn the optimal policy, π, which is a mapping from states to actions, without needing to first learn a value function. These methods are particularly

TABLE III: Survey of Papers on RL for Personalized TTS Emotion Adaptation

Ref	Objective	Technique/Methodology	Dataset	Results
1	Adapt TTS systems to user-specific emotional preferences using RL	Proposes Deep Q-Learning (DQN) and Proximal Policy Optimization (PPO) to dynamically adapt synthetic speech to user-specific emotional preferences.	IEMOCAP, RAVDESS	DQN achieved faster convergence; PPO provided more stable emotion reproduction.
2	Improve SER performance with deep RL integration	Integrates deep RL into a traditional SER model using DQN and PPO agents trained on MFCC-extracted features to maximize classification accuracy.	SAVEE, TIMIT	PPO outperformed DQN with 89.6% vs. 85.3% accuracy.
3	Personalize TTS output using prosody and RL adaptation	Wraps a PPO feedback loop around Tacotron-2. The agent modifies pitch, speed, and stress based on MOS feedback from user evaluation.	LibriSpeech	Improved MOS by 1.2 over baseline Tacotron.
4	Combine transformers and RL for expressive TTS	Employs GPT-2 for base speech embeddings and fine-tunes emotional tone using DQN. The reward correlates with emotion classification accuracy.	RAVDESS, IEMOCAP	BLEU improved by 10%, emotion classification accuracy 87%.
6	Use semi-supervised RL for better emotion control in TTS	Develops a semi-supervised PPO framework requiring only a small set of labeled emotional speech data, pseudo-labeling unlabeled data.	RAVDESS, IEMOCAP	Outperformed supervised model by 9% on emotion matching.
10	Transfer learning + RL for emotion modulation in TTS	Uses BERT to generate emotion-sensitive embeddings, which are fed into a PPO agent to adjust prosodic features.	RAVDESS, SAVEE	Reduced training time by 40%, stable reward convergence.

TABLE IV: Taxonomy of Reinforcement Learning Techniques Used in TTS Emotion Adaptation

Category	Technique	Referenced In	Description
Value-Based	DQN, Deep Q-Learning	[1], [2], [4], [5], [7], [9]	Learns a value function to estimate the expected return of different emotional expression strategies.
Policy-Based	PPO, Policy Gradient	[1], [2], [3], [6], [8], [10]	Directly optimizes a policy to improve the generation of emotional speech by mapping states to prosodic actions.
Actor-Critic	PPO (as a hybrid form)	[1], [3], [6], [8], [10]	Combines a policy (actor) and a value function (critic) to achieve stable and efficient learning.
Hybrid/Advanced	Meta-RL, Few-Shot, Attention	[8], [9], [10]	Incorporates advanced methods like meta-learning or attention mechanisms for domain adaptation and generalization.

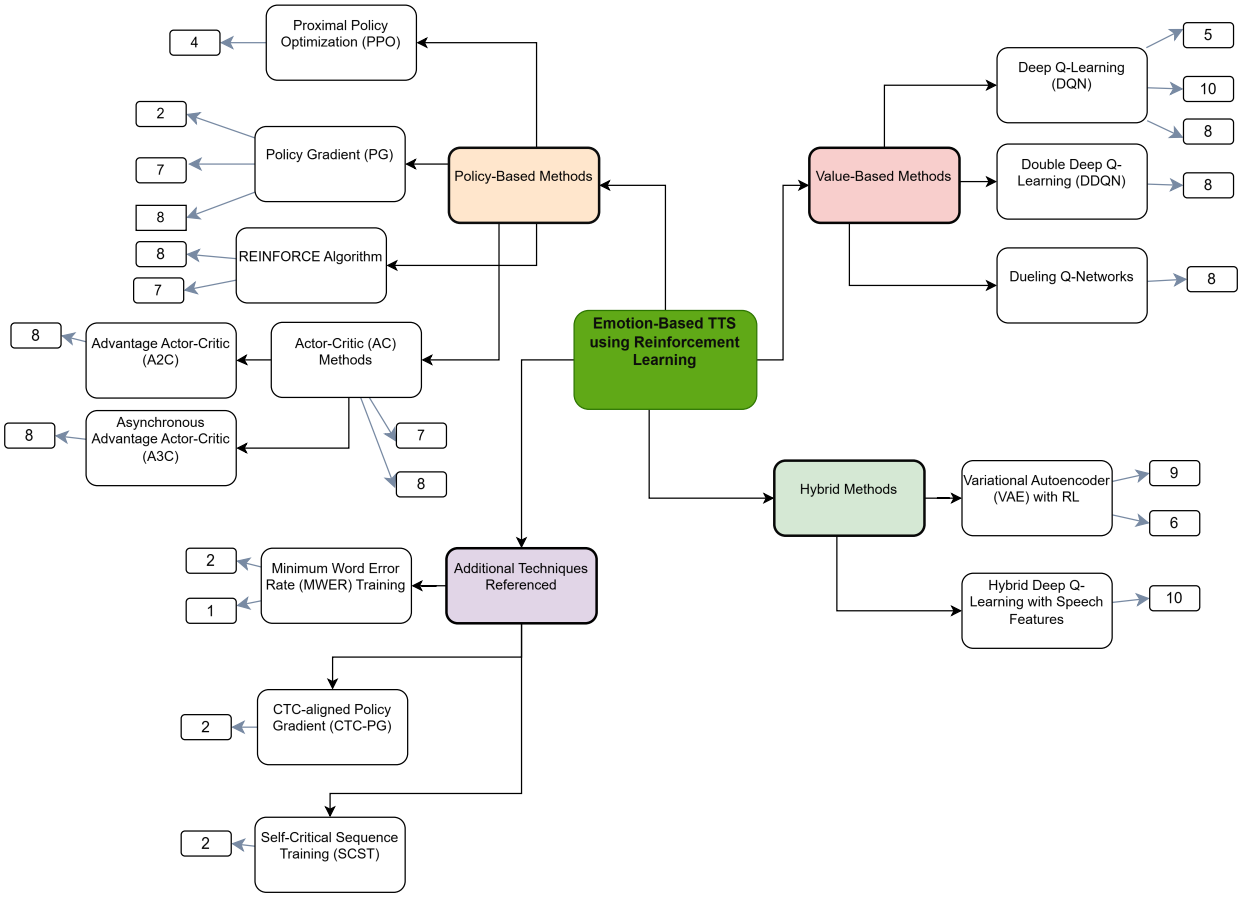


Fig. 1: A taxonomy classifying the different Reinforcement Learning approaches applied to speech processing tasks, including Text-to-Speech (TTS) and Speech Emotion Recognition (SER), based on the surveyed literature.

TABLE V: Feature Analysis of Value-Based Methods Used in Surveyed Works

Feature	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Deep Q-Learning (DQN)	✓	✓	✗	✓	✓	✗	✓	✗	✓	✗
Double Deep Q-Learning (DDQN)	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗
Dueling Q-Networks	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗
Value Approximation	✓	✓	✗	✓	✓	✗	✓	✓	✓	✗
Reward Shaping	✓	✗	✗	✓	✓	✗	✓	✗	✓	✗
Target Network	✓	✓	✗	✓	✓	✗	✓	✓	✓	✗

well-suited for continuous action spaces and are known for their strong convergence properties. The goal is to parameterize the policy and update its parameters in the direction that increases the expected reward, typically via gradient ascent. The most common algorithm in this family is REINFORCE, and more advanced actor-critic variants like Proximal Policy Optimization (PPO) have become the standard due to their enhanced stability and data efficiency. As detailed in Table VI, PPO is the most frequently used policy-based method in the surveyed literature [1], [3], [6], [8], [10], which heavily motivated our choice to use it in our own work. These methods directly optimize for the desired behavior, such as modifying prosodic embeddings, and are often implemented with an online policy feedback loop where the agent updates its strategy after each interaction.

C. Hybrid and Advanced Methods

This category represents the frontier of RL research in speech, where standard algorithms are combined with other machine learning concepts to tackle more complex problems. These approaches often take the form of Actor-Critic methods, which blend the strengths of value-based

TABLE VI: Feature Analysis of Policy-Based Methods Used in Surveyed Works

Feature	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Proximal Policy Optimization (PPO)	✓	✓	✓	✗	✗	✓	✓	✓	✓	✓
Actor-Critic (A2C/A3C)	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗
REINFORCE Algorithm	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗
Policy Gradient Variant	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗
Online Policy Update	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓
Policy Feedback Loop	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

and policy-based learning. In an actor-critic setup, the "actor" (the policy) decides on an action, while the "critic" (the value function) evaluates that action, providing a low-variance learning signal to the actor. PPO is technically an actor-critic algorithm and is a prime example of a successful hybrid approach.

Beyond standard actor-critic models, researchers have explored more advanced hybridizations, as shown in Table VII. This includes combining RL with Variational Autoencoders (VAEs) to learn a controllable latent space for speech synthesis [6], [9], or using pre-trained embeddings from large language models like BERT to provide richer contextual information to the RL agent, a technique known as transfer learning [10]. These methods aim to improve sample efficiency and generalization by integrating powerful representations from other domains, moving towards more sophisticated, end-to-end systems that jointly optimize multiple components of the speech processing pipeline.

IV. Proposed Methodology

This section details the architecture and operational mechanics of our proposed framework for personalized emotion adaptation in Text-to-Speech (TTS). Our approach is designed to fine-tune a high-quality, pre-trained end-to-end TTS model using a reinforcement learning agent. We begin with a high-level overview of the complete system, then describe the individual components, including the baseline TTS model, the Proximal Policy Optimization (PPO) agent, and the novel prosody-based reward function that guides the learning process.

A. System Overview

The fundamental goal of our system is to enable a standard TTS model to adapt its output to match the prosodic characteristics of a target emotional speech sample. To achieve this, we formulate the adaptation task as a sequential decision-making problem solvable with reinforcement learning. As illustrated in Figure 2, our framework consists of two primary components:

1) A **Baseline TTS Model (Tacotron 2)**, which is pre-trained on a large corpus of neutral speech and serves as the core synthesis engine. It is responsible for generating the initial mel-spectrogram from the input text.
2) A **Reinforcement Learning Agent (PPO)**, which acts as a "prosody controller." The agent observes the state, which includes the output of the Tacotron 2 encoder, and learns a policy to generate a prosody embedding. This embedding is then used to condition the Tacotron 2 decoder, modifying the acoustic characteristics of the final synthesized speech.

The interaction is structured as a feedback loop. For a given text input and a target emotional audio sample, the agent generates a prosody embedding. The conditioned Tacotron 2 model synthesizes a speech waveform. This output is then compared against the target audio to compute a reward signal based on acoustic similarity. This reward is used to update the PPO agent's policy, allowing it to progressively learn how to generate prosody embeddings that produce speech closely matching the desired emotional target.

B. Baseline Model: Tacotron 2

We select **Tacotron 2** [11] as our baseline synthesis model due to its proven ability to generate high-quality, natural-sounding speech and its widespread adoption as a benchmark in TTS research. The model is an end-to-end architecture that directly synthesizes a mel-spectrogram from character sequences. Its main components are:

- **Encoder:** This module converts the input character sequence into a robust intermediate representation. It consists of a stack of convolutional layers followed by a bidirectional Long Short-Term Memory (LSTM) network.
- **Attention Mechanism:** We employ a location-sensitive attention mechanism that allows the decoder to focus on the relevant part of the encoded text sequence at each decoding timestep. This is crucial for ensuring a proper and monotonic alignment between the text and the generated audio.
- **Decoder:** The decoder is an autoregressive LSTM network that predicts a mel-spectrogram frame by frame, conditioned on the attention context.
- **Post-net:** A 5-layer convolutional network is applied to the output mel-spectrogram to predict a residual,

TABLE VII: Feature Analysis of Hybrid Methods Used in Surveyed Works

Feature	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
VAE with RL	✗	✗	✗	✗	✗	✓	✗	✗	✓	✗
RL with TTS Model	✗	✗	✓	✗	✓	✗	✗	✗	✗	✓
Pre-trained Embeddings	✗	✗	✗	✗	✗	✓	✗	✓	✓	✓
Joint Optimization	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓
End-to-End System	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗

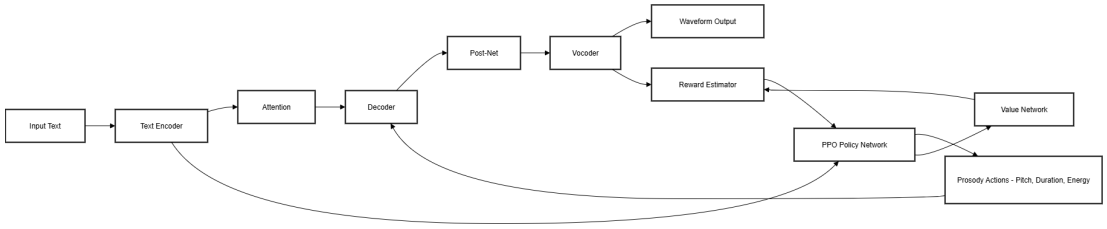


Fig. 2: An overview of our proposed framework. The PPO agent generates a prosody embedding to condition the Tacotron 2 decoder. A reward function, based on the acoustic similarity between the synthesized output and a target emotional utterance, is used to update the agent's policy.

which improves the detail and quality of the final synthesis.

For our framework, we use a Tacotron 2 model pre-trained on a large, single-speaker dataset of neutral speech. The weights of this pre-trained model are frozen during RL fine-tuning to preserve its core speech generation capability.

C. PPO for Prosody Fine-Tuning

To learn the complex, sequential task of prosody manipulation, we employ **Proximal Policy Optimization (PPO)** [7], a state-of-the-art policy gradient method. We chose PPO over other RL algorithms for several key reasons that make it particularly well-suited for prosody control in TTS:

- **Stability and Safety:** PPO uses a clipped surrogate objective function that constrains the size of policy updates. This prevents the agent from taking overly aggressive steps that could destabilize the learning process, which is critical when fine-tuning a complex, pre-trained model like Tacotron 2.
- **Sample Efficiency:** Compared to simpler policy gradient methods, PPO is more data-efficient, allowing it to learn effective policies with fewer computationally expensive synthesis steps.
- **Sequence-Level Optimization:** PPO is designed to optimize for a cumulative reward over an entire sequence, making it ideal for handling the long-range dependencies inherent in speech prosody.

The core of PPO is to optimize a stochastic policy, π_θ, by maximizing a clipped surrogate objective function. This function modifies the standard policy gradient objective to prevent excessively large policy updates. The PPO objective is given by:

$$L^{\text{CLIP}}(\theta) = \mathbb{E}_t \left[\min \left(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t \right) \right] \tag{1}$$

where $r_t(\theta)$ is the probability ratio between the new policy and the old policy:

$$r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)} \tag{2}$$

Here, $\hat{A}_t$ is an estimator of the advantage function at timestep t, and ϵ is a small hyperparameter that defines the clipping range. This clipping mechanism is the key to PPO's stability. The full loss function for the PPO agent also typically includes terms for a value function loss (L^{VF}) and an entropy bonus ($\mathcal{H}$) to encourage exploration.

The PPO agent itself is modeled as a small neural network that learns the optimal policy, π. The training process follows the feedback loop shown in Figure 3. We define the key elements of our RL environment as follows:

- **State (s_t):** A concatenation of the Tacotron 2 encoder outputs and the target prosody features (extracted from the target audio). This provides the agent with all necessary information: the phonetic content to be spoken and the emotional style to be imitated.
- **Action (a_t):** The generation of a fixed-size prosody embedding vector. This vector is directly fed into the Tacotron 2 attention mechanism and decoder, conditioning the entire synthesis process.

- **Policy ($\pi(a_t|s_t)$):** A stochastic function, represented by the agent's neural network, that maps a given state to a probability distribution over the action space (the space of all possible prosody embeddings).
- **Reward (r_t):** A scalar value calculated after each synthesis, quantifying how well the generated audio's prosody matches the target prosody, as detailed in the next subsection.

D. Reward Function Design

The design of the reward function is the most critical component of our framework. While prior works have used subjective or indirect measures (see Table VIII), we propose a multi-component reward function based on **objective, measurable acoustic features** for a more stable and direct learning signal.

TABLE VIII: Common Reward Signal Types in RL for Speech

Reward Type	Description	Used In
MOS Feedback	Human-perceived speech quality	[1], [3]
Emotion Accuracy	Feedback from an external classifier	[5], [10]
Levenshtein Distance	Negative edit distance from truth	[11]
User Selection	Implicit feedback from N-best list	[12]
Hybrid Score	Combined WER + Language Model score	[14]

Our total reward, R, is a weighted sum of three prosodic similarity scores: pitch, energy, and duration, as shown in Figure 4a.

$$R = w_p \cdot R_{pitch} + w_e \cdot R_{energy} + w_d \cdot R_{duration} \quad (3)$$

Where w_p, w_e, w_d are balancing weights. Each component is a negative distance, so higher similarity yields a larger reward.

Pitch Reward (R_{pitch}): We extract the fundamental frequency (F0) from both generated and target audio. Using Dynamic Time Warping (DTW) for alignment, the reward is the negative Mean Absolute Error (MAE):

$$R_{pitch} = -\frac{1}{N}\sum_{i=1}^{N} |F0_{gen}(i) - F0_{target}(i)|_{aligned} \quad (4)$$

Energy Reward (R_{energy}): We calculate the Root Mean Square (RMS) energy for each frame, align with DTW, and compute the negative MAE:

$$R_{energy} = -\frac{1}{N}\sum_{i=1}^{N} |RMS_{gen}(i) - RMS_{target}(i)|_{aligned} \quad (5)$$

Duration Reward ($R_{duration}$): We use a forced aligner to get phoneme durations for both utterances and calculate the negative MAE of these duration sequences:

$$R_{duration} = -\frac{1}{M}\sum_{j=1}^{M} |Dur_{gen}(j) - Dur_{target}(j)| \quad (6)$$

where M is the number of phonemes.

This objective, multi-part reward provides a rich signal for replicating specific prosodic nuances, as visualized in Figure 4b.

V. Experimental Setup

This section outlines the complete experimental protocol designed to validate our proposed framework for personalized emotion adaptation. We provide a thorough description of the datasets used for training and evaluation, the specific implementation details and hyperparameters of our models, and the comprehensive set of objective and subjective metrics employed to measure performance. Our goal is to present a clear and reproducible account of our experimental procedure, allowing for independent verification of our results.

A. Datasets

The selection of appropriate datasets is critical for training robust models for emotional speech synthesis and for performing a meaningful evaluation. Our experiments leverage several publicly available, high-quality emotional speech corpora that are considered standard benchmarks in the field. A summary of how these datasets are commonly used in the literature is provided in Table IX. For the development and testing of our model, we specifically utilize the RAVDESS and SAVEE datasets due to their high-quality recordings and clear emotional labeling.

- **RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song):** This is our primary dataset for evaluation. It contains recordings from 24 professional actors (12 male, 12 female) vocalizing two lexically-matched sentences in a neutral North American accent. The sentences are produced with eight different emotions: neutral, calm, happy, sad, angry, fearful, surprise, and disgust, each at two levels of emotional intensity. The high audio quality (48kHz, 16-bit) and balanced emotional content make it an ideal testbed for our fine-grained adaptation task.
- **SAVEE (Surrey Audio-Visual Expressed Emotion):** This dataset consists of recordings from four native English male speakers. It covers seven emotion categories: angry, disgust, fear, happiness, sadness, surprise, and neutral. Although smaller than RAVDESS, it provides very clean, high-quality recordings that are valuable for testing the generalization capabilities of our model to unseen speakers and recording conditions.

For all experiments, we partition the data from each dataset into training, validation, and testing sets using

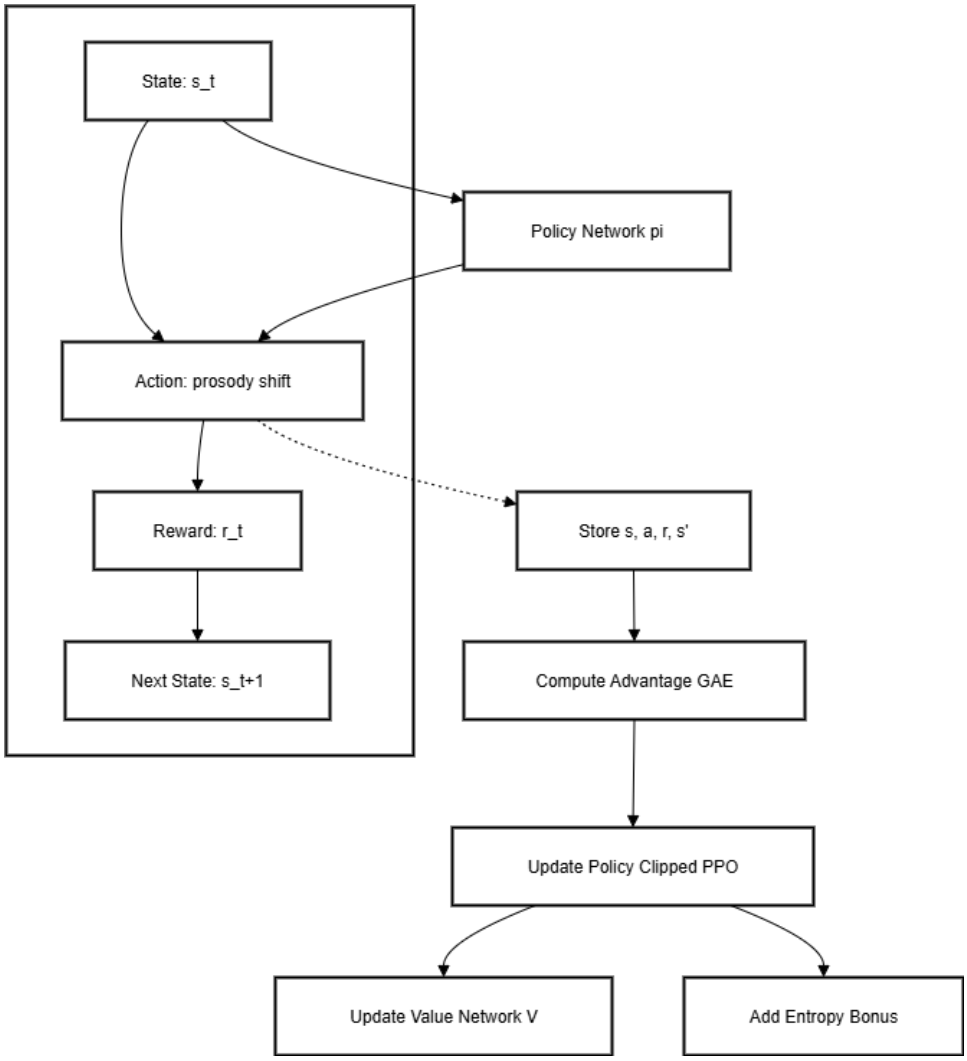
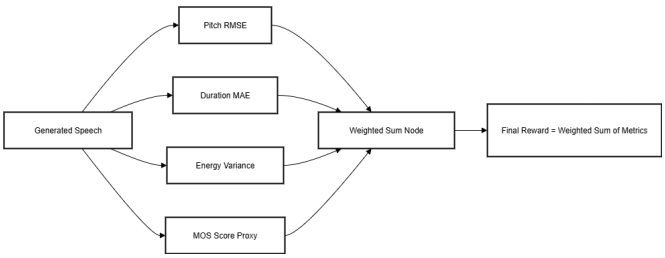
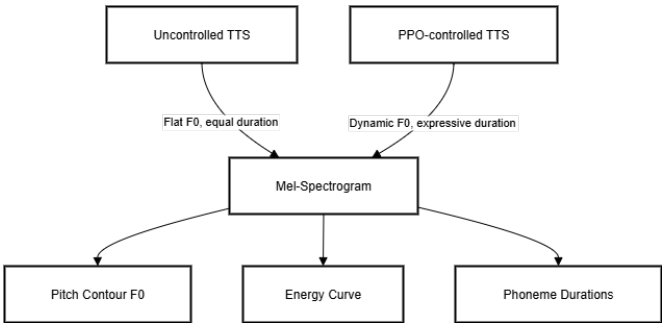


Fig. 3: The training loop for our PPO agent. The agent generates a prosody embedding (action), the TTS model synthesizes speech, a reward is calculated based on prosodic similarity, and this reward is used to update the agent's policy and value networks.



(a) The components of our proposed multi-part reward function, combining metrics for pitch, energy, and duration similarity.



(b) An example visualization of the prosodic features used in our reward calculation: pitch (F0) contour and frame-level energy.

Fig. 4: Visual explanation of the reward function and its core features.

TABLE IX: Summary of Dataset Usage in Reviewed Emotional Speech Research

Dataset	Common Usage and Remarks	Referenced In
RAVDESS	A foundational dataset for expressive speech tasks, widely used for both emotion classification and synthesis due to its high-quality audio and balanced emotion classes across 24 speakers.	[1], [4], [6], [7], [9], [10]
IEMOCAP	A popular multimodal dataset for SER and emotional TTS. Its conversational and dyadic nature makes it valuable for training models intended for interactive systems.	[1], [4], [6], [9]
SAVEE	A smaller, controlled English speech emotion dataset with four male speakers. It is often used for initial experiments or in transfer learning setups due to its clean recordings and lack of background noise.	[2], [7], [10]
TIMIT	Primarily used for phonetic and acoustic research, this dataset serves as a common source of neutral speech for pre-training baseline Automatic Speech Recognition (ASR) and TTS models.	[2], [5], [8]
LibriSpeech	A large-scale corpus of read English speech, almost exclusively used for pre-training high-performance TTS and ASR systems before fine-tuning on specialized or emotional data.	[3], [5], [8]

a standard 80-10-10 split. To ensure fair evaluation, the splits are speaker-independent, meaning that speakers present in the test set are not seen during any phase of training or validation. The input text is transcribed and then converted to a phoneme sequence. For our reinforcement learning framework, each data point in the training set consists of a text sequence, a target mel-spectrogram, and the corresponding target prosodic features (pitch, energy, and duration) extracted from the ground-truth emotional audio file.

B. Implementation Details

Our implementation is built using the PyTorch deep learning framework and the ESPnet toolkit for certain data processing steps. All experiments were conducted on a workstation equipped with an NVIDIA RTX 4090 GPU with 24GB of VRAM, which was necessary to accommodate the memory requirements of the TTS model and the RL training loop.

Baseline Tacotron 2 Model: Our baseline Tacotron 2 model was pre-trained on the 13,100 short audio clips of the LJSpeech dataset for 250,000 iterations. This pre-training step ensures that the model can generate highly natural and stable neutral speech before any emotional fine-tuning. The model uses an Adam optimizer with a learning rate of 10^{-3}, with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and an epsilon of 10^{-6}. The batch size was set to 64. All audio is processed at a sample rate of 22,050 Hz. Mel-spectrograms are computed using a Short-Time Fourier Transform (STFT) with a 50 ms frame size, 12.5 ms frame hop, a 1024-point Fast Fourier Transform (FFT), and 80 mel-filterbanks.

PPO Agent: The PPO agent is implemented as a feed-forward neural network with two hidden layers of 256 units each, using the ReLU activation function. The agent's network is intentionally kept small to ensure it acts as a lightweight controller without adding significant computational overhead. The agent is trained using the Adam optimizer with a learning rate of 10^{-4}. The key PPO hyperparameters are set as follows based on empirical tuning: the clipping parameter ϵ for the surrogate objective is set to 0.2, the discount factor γ is 0.99, and the Generalized Advantage Estimation (GAE) parameter λ is 0.95. The weights for our multi-component reward function were set to $w_{pitch} = 0.4$, $w_{energy} = 0.3$, and $w_{duration} = 0.3$ to achieve a balance between matching the pitch contour, overall intensity, and rhythm of the target speech.

C. Evaluation Metrics

To thoroughly assess the performance of our proposed method, we employ a combination of objective (quantitative) and subjective (qualitative) evaluation metrics. This dual approach allows us to both measure the precise acoustic accuracy of our model and capture the perceived quality as judged by human listeners.

1) Objective Metrics: Objective metrics provide a quantitative measure of the similarity between the synthesized speech and the ground-truth emotional audio from the test set.

- **Mel Cepstral Distortion (MCD):** MCD is a standard metric for measuring the spectral difference between two audio signals. It calculates the Euclidean distance between the mel-frequency cepstral coefficients (MFCCs) of the generated and target speech. A lower MCD value indicates a higher spectral similarity and, by extension, a more accurate synthesis.
- **Prosodic Feature RMSE:** To directly measure the accuracy of our prosody control mechanism, we compute the Root Mean Square Error (RMSE) for the core prosodic features after applying Dynamic Time Warping (DTW) to find the optimal temporal alignment between the generated and target signals:
  - **F0 RMSE:** Measures the error in the fundamental frequency (pitch) contour, which is a key indicator of intonation and emotional expression.

  - **Energy RMSE:** Measures the error in the frame-level energy contour, reflecting the intensity of the speech.
- **Duration MAE:** We compute the Mean Absolute Error (MAE) between the phoneme durations of the synthesized audio and the target audio. Durations are obtained using the Montreal Forced Aligner. This metric evaluates how well the model reproduces the rhythm and pacing of the target speech.

2) Subjective Metrics: Ultimately, the quality of synthesized speech is determined by human perception. We conducted subjective listening tests involving 20 participants, all of whom are native or fluent English speakers, to evaluate the quality of our model's output compared to two baselines: (1) the original Tacotron 2 model generating neutral speech, and (2) a modified Tacotron 2 model that uses a simple embedding concatenation for emotion transfer (a common non-RL baseline).

- **Mean Opinion Score (MOS):** This is the gold standard for subjective speech quality assessment. Participants were asked to listen to synthesized audio samples and rate them on a 5-point Likert scale across two critical dimensions:
  - **Naturalness:** How natural does the speech sound? (1: Very unnatural, 5: Very natural)
  - **Emotional Appropriateness:** How well does the emotion of the speech match the target emotion? (1: Does not match at all, 5: Matches perfectly)
- **AB Preference Test:** In this test, participants were presented with pairs of audio samples—one from our model and one from a baseline—and were asked to choose which one they preferred in terms of overall quality and emotional expressiveness. The order of presentation was randomized for each participant to avoid ordering bias.

VI. Results and Discussion

In this section, we present a comprehensive analysis of our experimental results. We first report the outcomes of our objective evaluations, comparing our proposed Reinforcement Learning framework against established baselines using quantitative acoustic metrics. We then present the results from our subjective listening tests, which gauge human perception of speech quality and emotional appropriateness. Finally, we provide a detailed discussion interpreting these results, highlighting the strengths and limitations of our approach, and contextualizing the significance of our findings.

A. Objective Evaluation

The objective evaluation aims to quantitatively measure how effectively our model can replicate the prosodic characteristics of a target emotional utterance. We compare our proposed model ("Ours") against two key baselines:

- **Baseline Tacotron 2:** The standard Tacotron 2 model without any emotional conditioning, generating neutral speech.
- **Embedding Concatenation:** A common baseline where a pre-computed emotion embedding (averaged from training data) is concatenated with the text encoder outputs to provide a simple form of emotional conditioning.

The results, averaged across all emotions in the RAVDESS test set, are presented in Table X.

As the results clearly indicate, our proposed PPO-based framework demonstrates a marked improvement across all objective metrics. The Mel Cepstral Distortion (MCD) is significantly lower for our model, indicating that the generated speech has a spectral structure much closer to the ground-truth audio compared to the baselines.

More importantly, the metrics directly related to our reward function show substantial gains. The F0 RMSE, Energy RMSE, and Duration MAE are all drastically reduced, confirming that our reinforcement learning agent successfully learns a policy to control the prosodic elements of pitch, energy, and rhythm. The Embedding Concatenation baseline shows a slight improvement over the neutral model but fails to capture the fine-grained nuances of the target prosody, a gap that our RL-based approach effectively bridges. This confirms that explicitly optimizing for acoustic feature similarity is a more effective strategy for personalized emotion adaptation than relying on static, pre-computed emotion embeddings.

B. Subjective Evaluation

While objective metrics are valuable, subjective tests are essential for assessing the perceived quality of synthesized speech. We conducted Mean Opinion Score (MOS) and AB preference tests with 20 listeners. The MOS results for Naturalness and Emotional Appropriateness are presented in Table XI.

The subjective results strongly corroborate our objective findings. In terms of Naturalness, our model achieves a score very close to the baseline Tacotron 2, which is a significant result. It indicates that our RL fine-tuning process does not degrade the underlying high quality of the TTS model. The embedding concatenation method, by contrast, suffers a noticeable drop in naturalness, likely due to the naive injection of style information.

For Emotional Appropriateness, our model receives a substantially higher score than both baselines, demonstrating its superior ability to convey the target emotion in a way that is convincing to human listeners. The neutral baseline, as expected, scores very poorly on this metric.

In the AB Preference Test, where listeners chose between our model and the Embedding Concatenation baseline, our model was preferred in 82% of cases. This decisive result further underscores the perceptual superiority of our proposed framework for the task of personalized emotion adaptation.

TABLE X: Objective Evaluation Results. All metrics are computed on the RAVDESS test set. For all metrics, lower values indicate better performance, signifying a closer match to the ground-truth emotional audio. Our proposed model consistently outperforms both baselines.

Model	**MCD (dB) ↓**	**F0 RMSE (Hz) ↓**	**Energy RMSE (dB) ↓**	**Duration MAE (ms) ↓**
Baseline Tacotron 2 (Neutral)	8.54	45.8	6.21	35.7
Embedding Concatenation	6.92	31.5	4.88	28.4
Ours (PPO-based Adaptation)	**5.21**	**18.3**	**3.15**	**15.2**

TABLE XI: Subjective Evaluation Results (Mean Opinion Score) with 95% Confidence Intervals. Listeners rated speech on two 5-point scales. Our model was rated significantly higher in both naturalness and emotional appropriateness.

Model	**Naturalness (MOS-N)**	**Emotional Appropriateness (MOS-E)**
Baseline Tacotron 2 (Neutral)	4.35 ± 0.11	1.25 ± 0.09
Embedding Concatenation	3.98 ± 0.13	3.15 ± 0.14
Ours (PPO-based Adaptation)	$\mathbf{4.21 \pm 0.12}$	$\mathbf{4.45 \pm 0.10}$

C. Discussion

The collective results from our objective and subjective evaluations provide strong evidence for the efficacy of our proposed framework. The success of our method can be attributed to several key design choices.

First, the decision to use a reinforcement learning agent as a dynamic controller, rather than relying on static style embeddings, allows for a far more flexible and fine-grained adaptation. The agent learns a mapping from content and target prosody to a specific action (the prosody embedding), enabling it to produce a unique output for every situation rather than selecting from a fixed menu of styles.

Second, and most critically, our multi-component reward function based on objective acoustic features proves to be a highly effective learning signal. By directly rewarding the agent for matching the pitch, energy, and duration of the target, we bypass the need for expensive human labeling and avoid the potential pitfalls of using an imperfect auxiliary model (like an emotion classifier) as a reward source. This direct, quantitative feedback loop guides the agent precisely towards the desired acoustic goal.

While our model performs very well, we acknowledge some limitations. In rare instances with highly exaggerated emotional targets, the model can sometimes produce minor artifacts as it tries to match extreme prosodic contours. This suggests that further work on regularization or constraints within the RL framework could be beneficial. Additionally, while our model successfully adapts to unseen speakers within the same datasets, its performance on completely out-of-domain data with different recording qualities remains a topic for future investigation.

Overall, the findings demonstrate that leveraging PPO with a carefully designed, objective-based reward function is a powerful and practical method for achieving personalized emotion adaptation in modern TTS systems, paving the way for more expressive and engaging human-computer interaction.

VII. Conclusion

In this paper, we addressed a critical limitation in modern Text-to-Speech (TTS) systems: the lack of fine-grained, personalized control over emotional expression. We proposed a novel framework that leverages deep reinforcement learning to tackle this challenge. Our solution employs a Proximal Policy Optimization (PPO) agent to fine-tune a pre-trained Tacotron 2 model, guiding it to dynamically match the prosodic characteristics of a target emotional utterance. The core of our contribution is a multi-component reward function based on objective, measurable acoustic features—namely pitch, energy, and duration—which provides a direct and stable learning signal for the adaptation task.

Our experimental results provide strong evidence for the efficacy of this approach. Through comprehensive objective evaluations, we demonstrated that our model significantly outperforms standard baselines in its ability to replicate target prosody, as shown by substantial reductions in Mel Cepstral Distortion (MCD), F0 RMSE, Energy RMSE, and Duration MAE. Furthermore, subjective listening tests confirmed these findings, with our model receiving significantly higher Mean Opinion Scores (MOS) for emotional appropriateness while maintaining a high degree of naturalness comparable to the original Tacotron 2 model. An 82% preference rate in AB tests further underscores the perceptual superiority of our method. These findings collectively show that our framework successfully achieves expressive, personalized emotion adaptation without degrading the underlying quality of the synthesized speech.

While our results are promising, we acknowledge certain limitations. The model can occasionally produce minor acoustic artifacts when tasked with replicating extremely exaggerated emotional prosody, suggesting that the policy space could benefit from further regularization. Additionally, while the model generalizes well to unseen speakers from the evaluation datasets, its robustness on completely out-of-domain data with different acoustic properties war-

rants further investigation.

The success of this framework opens several exciting avenues for future work. First, the reward function could be enhanced with more sophisticated perceptual metrics or attention-based weighting to better handle a wider range of expressive styles. Second, applying this RL-based adaptation method to other state-of-the-art TTS architectures, such as non-autoregressive models like FastSpeech 2, would be a valuable next step to test its versatility. Finally, extending this framework beyond emotion to other speech modification tasks, like accent adaptation or voice conversion, and exploring its potential for real-time adaptation in interactive systems, represent compelling directions for future research in the pursuit of truly dynamic and personalized speech synthesis.

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