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A Prosody-Driven Extension to Embedding-Guided Neural Voice Conversion for Natural and Expressive Speech Synthesis

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Abstract **- Recent advancements in voice conversion systems have been largely driven by deep learning techniques, enabling the high-quality synthesis of human speech. However, existing models often fail to generate emotionally expressive speech, resulting in outputs that lack the richness of human communication. The main goal of this research is to fill this gap by incorporating a prosody-aware extension into embedding-guided neural voice conversion (EGNVC). This extension seeks to improve the emotional expressiveness and naturalness of the converted speech, while preserving both speaker identity and linguistic content. A new framework is introduced that integrates a content encoder, speaker embedder, and prosody extractor to address this challenge. The prosody extractor is designed to capture dynamic prosodic elements like pitch, energy, and timing from a reference audio signal. These features are then introduced into the decoding process through a prosody conditioning module, allowing for precise control over prosody during speech synthesis. FiLM (Feature-wise Linear Modulation) layers are employed to adjust intermediate features based on speaker and prosody embeddings, ensuring that both the speaker's identity and the intended prosodic qualities are accurately maintained. The vocoder converts the generated mel-spectrograms into high-quality waveforms, ensuring a natural-sounding output. Experimental results show that the proposed model surpasses conventional voice conversion systems in maintaining linguistic content and prosodic features, with significant improvements in Mel-Cepstral Distortion (MCD), Pitch RMSE, and Energy RMSE. Subjective assessments, including Mean Opinion Score (MOS) and Emotion Classification Accuracy, highlight the model's enhanced emotional expressiveness and naturalness. These findings emphasize the critical role of prosody in high-quality voice conversion, offering a robust framework for creating more dynamic, expressive, and human-like speech synthesis systems.**

Keywords - Voice Conversion, Prosody, Deep Learning, Speech Synthesis, Embedding-Guided Neural Voice Conversion, Emotion Recognition

I. INTRODUCTION

This template, The field of voice conversion has witnessed substantial advancements in recent years, particularly with advent of deep learning techniques that enable high-fidelity synthesis of human speech [1]. Embedding-guided neural voice conversion (EGNVC) has emerged as promising approach by utilizing speaker and content embeddings to transfer voice characteristics from source speaker to target speaker without requiring parallel data. These models have demonstrated notable success in preserving speaker identity and linguistic content while enabling flexible and speaker-independent conversions. However, most conventional systems still struggle with generating natural-sounding and emotionally rich speech, often resulting in outputs that lack the expressiveness found in human communication [2].

Prosody, which includes elements like rhythm, stress, and intonation, is crucial for expressing emotions, conveying speaker intent, and capturing the subtleties of conversation [3]. The absence of accurate prosodic modeling in neural voice conversion frameworks leads to monotonic and unnatural speech, even when the content and speaker identity are well-preserved. This shortcoming becomes especially pronounced in expressive speech scenarios such as storytelling, dialogue synthesis, or emotional speech generation, where prosody is as important as lexical content. Despite progress in embedding-based approaches, most systems fail to integrate prosodic features in a meaningful and controllable manner.

A major challenge in enhancing prosodic expressiveness lies in the difficulty of accurately capturing and transferring prosodic features between speakers [4]. Traditional methods often depend on handcrafted features or rely on overly simplified representations of pitch and duration, which cannot fully model the intricacies of human prosody. Moreover, speaker embeddings, though effective at preserving identity, tend to collapse nuanced emotional and rhythmic cues into a fixed vector space, limiting the system's ability to synthesize dynamic and engaging speech [5]. These limitations underscore the need for a more nuanced and prosody-aware framework that can complement existing embedding-guided techniques.

Additionally, the disentanglement of prosodic information from linguistic and speaker characteristics poses a non-trivial research problem [6]. Capturing speaker-specific prosodic traits while maintaining cross-speaker generalizability demands robust architectural innovations and enhanced supervision during training. Without an explicit mechanism to model and guide prosody, voice conversion models risk producing flat or overly uniform outputs that fail to replicate the rich variability of real human speech [7]. Thus, there is an urgent requirement to design systems that explicitly model prosody as a distinct, controllable component in the voice conversion pipeline. The proposed *Prosody-Driven Extension to Embedding-Guided Neural Voice Conversion* addresses these challenges by

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integrating a prosody modeling module into the conventional EGNVC architecture. This extension is designed to learn explicit prosodic embeddings that capture pitch, energy, and timing variations at multiple granularities, enabling more expressive and contextually appropriate speech synthesis. By leveraging attention mechanisms and hierarchical encoders, the system achieves fine-grained prosodic control while maintaining speaker fidelity and linguistic clarity [8].This innovative integration improves the naturalness and emotional depth of converted speech, while also opening new possibilities for more human-like interactions in areas like virtual assistants, audiobook narration, and customized TTS systems..

II. LITERATURE SURVEY

First, Seungmin Choi et al. [9] presented Knowledge Graphs (KGs) as structured frameworks linking entities and relationships, widely used in NLP, recommendation systems, and medical diagnostics. Their integration with large language models (LLMs), especially to address hallucination issues, has gained momentum. This paper reviews post-2022 advancements in Knowledge Graph (KG) development, focusing on Extraction, Learning Paradigms, and Evaluation. It covers large-scale data preprocessing, multimodal extraction, and improved embeddings through Graph Neural Networks, Transformers, and LLMs. The evaluation section highlights intrinsic and extrinsic metrics, with a focus on interpretability and reliability.

Danyang Cao et al. [10] proposed NeuralVC, a real-time voice conversion model built upon VITS framework, where decoder plays a key role in optimizing speech synthesis speed. To ensure speaker-independent content extraction, the model employs a pre-trained HuBERT module for capturing speech content features. For faster synthesis, the authors integrate a streamlined neural decoder inspired by SEANet, modified to incorporate speaker identity, thereby improving the resemblance of the generated voice to the target speaker. Furthermore, a pre-trained speaker encoder is introduced alongside a speaker consistency loss function, enhancing the model's generalization to unfamiliar voices and enabling robust any-to-any speech conversion.

Xu Tan et al. [11] proposed NaturalSpeech, a TTS system achieving human-level quality on benchmark datasets. It uses variational auto-encoder (VAE) for end-to-end text-to-waveform generation. Important improvements include phoneme pre-training, differentiable duration modeling, bidirectional prior/posterior modeling, and a memory mechanism within the VAE. These advancements enhance the prior's expressiveness from text and simplify the posterior from speech. On the LJSpeech dataset, NaturalSpeech achieved a CMOS of -0.01, with a Wilcoxon signed-rank test ($p \gg 0.05$) showing no significant perceptual difference, making it the first TTS system to statistically match human speech quality.

Kun Zhou et al. [12] reviewed recent advancements in emotional voice conversion and speech databases. To meet growing demand, they introduced Emotional Speech Database (ESD), now publicly available for research. ESD contains 350 parallel utterances from 10 native English and 10 native Chinese speakers, covering five emotions: neutral, happy, angry, sad, and surprise. With over 29 hours of high-quality speech recorded in a controlled setting, database supports multi-speaker and cross-lingual emotional voice conversion studies. Authors also implemented several state-of-the-art voice conversion systems on the ESD dataset.

Chenfeng Miao et al. [13] introduced EfficientTTS 2 (EFTS2), which is an advanced one-stage, high-quality end-to-end text-to-speech (TTS) framework which is both fully differentiable and computationally efficient. The framework leverages adversarial training, integrating differentiable aligner and hierarchical variational autoencoder (VAE)-based waveform generator, thereby eliminating reliance on external alignment tools, invertible models, or intricate training procedures commonly found in earlier TTS approaches. In addition, the authors extend this architecture to the domain of voice conversion (VC) by proposing EFTS2-VC, an end-to-end solution capable of performing high-fidelity speech-to-speech transformation.

Mingyang Zhang et al. [14] introduced TTL-VC, a voice conversion method that learns from text-to-speech (TTS) system. The TTS model uses sequence-to-sequence architecture to map text into speaker-independent context vectors, which are then used to supervise the VC system. In the VC model, speech replaces text as input, but decoder remains similar and is conditioned on speaker embeddings. This enables any-to-any voice conversion using non-parallel data. During training, both TTS and VC systems are trained with text and speech respectively. At inference, the VC system functions independently without text. TTL-VC outperforms PPG and AutoVC in quality, naturalness, and speaker similarity.

Wei Zhao et al. [15] highlighted the role of speech synthesis in the Internet of Things (IoT), emphasizing its importance in enabling human-device interaction. While end-to-end TTS systems generate natural-sounding speech, existing parallel TTS frameworks often lose vital information and fail to convey rich emotional content. To overcome these limitations, the authors proposed Emo-VITS, an enhanced version of the VITS architecture. Emo-VITS integrates an emotion network that captures both global and local emotional cues from reference audio. These features are fused using an attention-based module. This approach enables more expressive and emotionally controlled speech synthesis. System aims to improve emotional realism and versatility of synthesized voices.

Wen-Chin et al. [16] presented latest Voice Conversion Challenge (VCC), focusing on singing voice conversion (SVC) and renamed it Singing Voice Conversion Challenge (SVCC). New dataset was created for in-domain and cross-domain SVC tasks. Over two months, 26 systems, including two baselines, were submitted. Listening tests showed that while top systems achieved near-human naturalness, none matched the target speakers in similarity. Cross-domain SVC was notably more challenging than in-domain, especially in retaining vocal similarity. Objective evaluation metrics were also analyzed, with only a few showing strong correlation with human perception. The study highlights ongoing challenges in achieving realistic and expressive voice conversion.

III. PROPOSED MODEL

The core innovation of our approach is the integration of prosody-aware design into a traditional embedding-guided neural voice conversion (VC) framework, enhancing the naturalness and emotional expressiveness of speech synthesis.

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This is achieved by extending the conventional content-encoder–speaker-decoder pipeline with two additional modules: a Prosody Extractor and a Prosody Conditioning Module. The Prosody Extractor is responsible for capturing rhythmic and intonational aspects of speech such as pitch, energy, and duration from either the source or a reference utterance. These prosodic features are encoded into a low-dimensional vector that reflects the expressive style of the input. Simultaneously, content encoder extracts linguistic information, and the speaker encoder captures target speaker's identity. All three representations linguistic content, speaker identity, and prosody are then effectively fused by the Prosody Conditioning Module, which guides the decoder in generating mel-spectrograms that preserve the intended meaning, speaker characteristics, and expressive tone. During training, the model learns to disentangle these aspects and recombine them accurately through end-to-end optimization. At inference, users can provide custom prosody inputs to impose desired speaking styles or emotional expressions on any source utterance, achieving highly flexible and controllable prosody transfer. This design allows for dynamic voice conversion with high naturalness, speaker fidelity, and emotional depth, as visualized in system architecture shown in Figure 1.

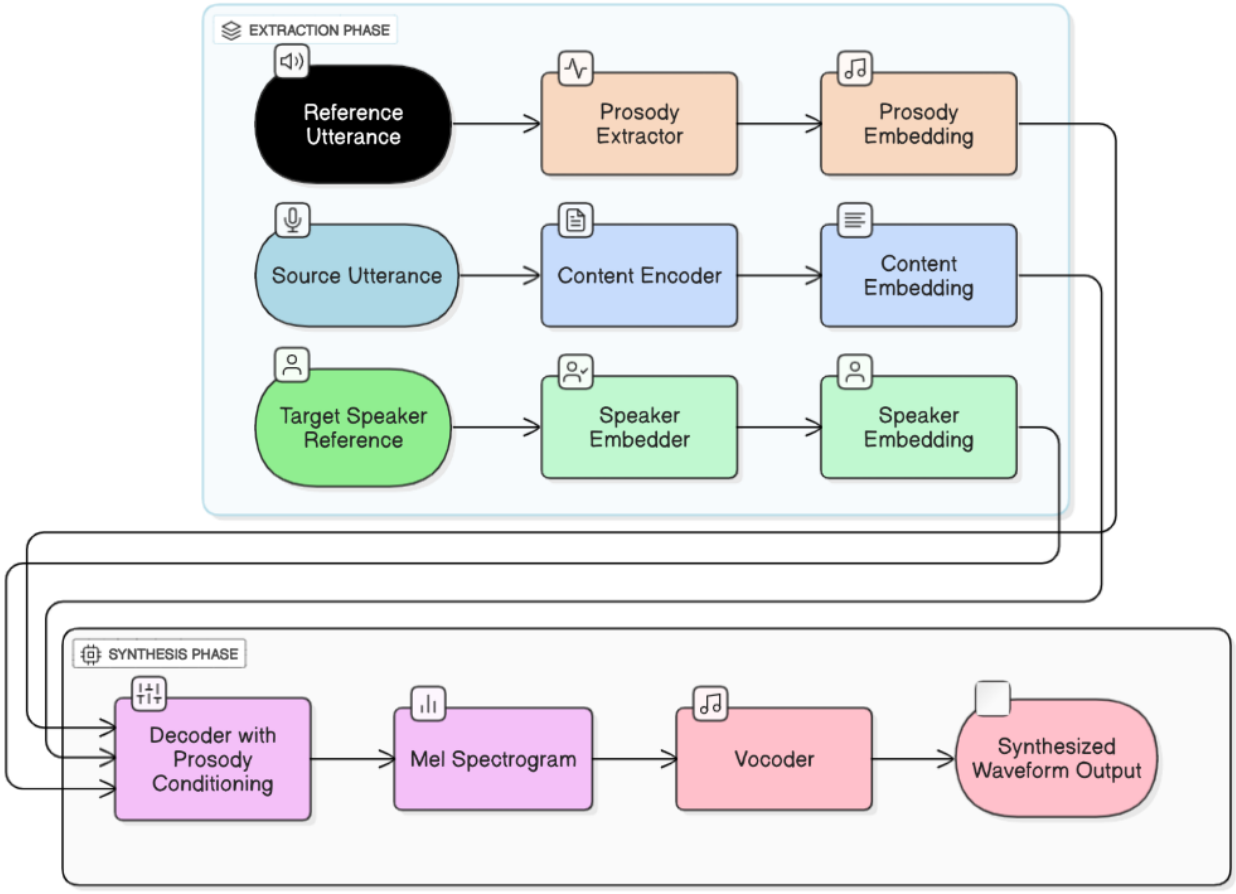

Figure 1: Proposed System Architecture

A. Content Encoder

The Content Encoder is a critical component responsible for extracting linguistic content from source utterance while discarding speaker-specific and prosodic features. It operates on the raw acoustic features, such as the mel-spectrogram, and learns to represent only the phonetic and structural aspects of speech, such as phonemes, syllables, and their sequential ordering. This content representation, denoted as $\boldsymbol{C}$, serves as the backbone for voice conversion since it encapsulates "what is being said" without "how it is said" or "who says it." The encoder typically consists of convolutional layers or recurrent neural networks (RNNs) to effectively model local and long-range dependencies in speech. By isolating linguistic information, encoder enables subsequent modules to independently manipulate voice identity and expressive style, ensuring that the core message remains unchanged during conversion.

B. Speaker Embedder

The **Speaker Embedder** is designed to capture unique vocal identity of target speaker, such as pitch range, timbre, and accent. Given short reference speech segment from target speaker, embedder generates a low-dimensional speaker embedding vector, denoted as , that summarizes these identity characteristics. This embedding allows model to recreate voice quality of target speaker even when the source content comes from a different individual. The speaker encoder can be based on pretrained models like d-vector, x-vector, or learnable embeddings trained jointly within the system. Resulting

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speaker vector acts as a conditioning factor for the decoder, ensuring that synthesized speech reflects vocal traits of intended speaker while retaining input content and incorporating external prosody if provided.

C. Prosody Extractor

The Prosody Extractor plays a central role in enhancing the naturalness and expressiveness of synthesized voice by capturing prosodic elements of a reference utterance. These elements include pitch contour (intonation), energy (loudness dynamics), and duration (timing and rhythm), which collectively shape the emotional tone and speaking style of an utterance. The extracted features are transformed into a compact vector embedding, denoted as *P*, which summarizes the expressive characteristics of the speech. This embedding is not dependent on the speaker identity or content, allowing it to be flexibly transferred across different utterances or speakers. The Prosody Extractor often employs recurrent or convolutional neural layers with attention mechanisms to effectively capture temporal variations and dynamic patterns across frames, enabling more expressive and contextually rich speech synthesis when combined with content and speaker information.

D. Decoder with Prosody Conditioning

The Decoder with Prosody Conditioning is the synthesis core of the model, responsible for generating mel-spectrogram that accurately reflects target speaker's voice and the imposed prosodic style. It takes the content representation C from the encoder and injects both the speaker embedding S and the prosody vector P using FiLM (Feature-wise Linear Modulation) layers. FiLM layers modulate the intermediatethe decoder to adjust its generation behavior dynamically. This architectural design ensures that the final spectrogram output not only maintains linguistic fidelity of source input but also aligns with target speaker's voice and expressive elements from the reference prosody. The decoder often uses autoregressive RNNs, Transformer blocks, or fully convolutional networks to generate high-quality frame-wise acoustic features.

feature maps by including learned affine transformations (scaling and shifting) based on *S* and *P*, effectively enabling

E.Vocoder

The **Vocoder** acts as the final stage in the pipeline, responsible for converting the generated mel-spectrogram into an audible waveform with high naturalness and clarity. Given that mel-spectrograms are intermediate time-frequency representations, the vocoder fills in the temporal resolution and generates raw audio samples at high sampling rates (e.g., 16kHz or 22kHz). Modern neural vocoders such as **HiFi-GAN**, **WaveGlow**, or **ParallelWaveGAN** are commonly used due to their ability to produce high-fidelity speech with low latency. The vocoder is either pretrained on a large speech corpus or fine-tuned using data aligned with the target speaker and prosody, ensuring consistency with the rest of the pipeline. By translating spectral features into real waveform signals, the vocoder brings the model's predictions to life, completing the process of prosody-aware neural voice conversion with speaker-specific and expressively rich speech output.

Algorithm Steps

A. Training Flow

1. Data Preparation

Prepare training data in the form of triplets:
$(-[[X_{src}, X_{tgt}, X_{pros})$

- X_{src} : A source speaker utterance containing the linguistic content to be preserved.
- X_{tgt} : A target speaker's utterance that provides speaker-specific identity features like timbre and tone.
- X_{pros} : A prosody-rich utterance used to extract emotional and rhythmic style (e.g., excitement, sadness, emphasis).

2. Content Encoding

Pass X_{src} through the **Content Encoder** to extract high-level linguistic features:
$C = ContentEncoder(X_{src})$

- This encoder removes speaker and prosody cues, isolating only the spoken message.
- The resulting content embedding CC captures phonetic structure for accurate linguistic preservation.

3. Speaker Embedding

Pass X_{tgt} through the **Speaker Embedder** to generate a target speaker vector:
$S = SpeakerEmbedder(X_{tgt})$

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- The speaker vector SS encodes the vocal characteristics unique to the target voice.
- This embedding is essential for re-synthesizing the content in the target speaker's voice.

4. Prosody Extraction

Process X_{pros} with the **Prosody Extractor** to compute time-aligned prosody features:
$P = ProsodyExtractor(X_{pros})$

- Extracts pitch contours, energy dynamics, and duration for each frame.
- This representation enables modeling of expressiveness, emotion, and rhythm in speech.

5. Prosody-Conditioned Decoding

Feed C into the decoder, conditioning it with S and P using FiLM layers:
$\hat{X} = Decoder_{FiLM}(C, S, P)$

- FiLM applies feature-wise modulation to incorporate speaker and prosody cues into decoding.
- Output is a mel-spectrogram that preserves content, mimics the target voice, and reflects expressive prosody.

6. Loss Computation

Calculate total loss using multiple components:

- **Reconstruction Loss**:
  $L_{rec}(\hat{X}, X_{tgt})$
  Ensures output spectrogram closely resembles the ground truth.
- **Cycle Consistency Loss**: Convert $\hat{X}$ back to source speaker and compare with X_{src}.
- **Speaker Classification Loss**: Classify $\hat{X}$ as belonging to speaker S.
- **Prosody Loss**: Ensure prosodic features in $\hat{X}$ match PP.
- **Adversarial Loss**: Improve naturalness using a GAN-style discriminator to distinguish real vs. generated speech.

7. Parameter Update

Backpropagate the total loss to update model weights.

- Gradients flow through the encoder, speaker embedder, prosody extractor, FiLM layers, and decoder.
- The model progressively learns to disentangle and recombine content, speaker, and prosody more effectively over training epochs.

B. Inference Flow

1. Input Collection

Collect the following inputs for inference:

- **Source Utterance $\mathbf{X_{src}}$** : Provides the content to be converted.
- **Target Speaker Reference X_{src}**: Short clip for identity embedding → S.
- **Optional Prosody Reference X_{src}**: Reference to extract prosody PP. If not available, use a neutral prosody vector $P_{default}$ for a flat speaking style.

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2. Encoding & Extraction

Encode and extract embeddings from inputs:

- Pass $\boldsymbol{X_{src}}$ into the Content Encoder to obtain content embedding CC.
- Use the Speaker Embedder on $\boldsymbol{X_{tgt}}$ to compute speaker embedding SS.
- If $\boldsymbol{X_{pros}}$ is provided, extract prosody embedding PP; otherwise, set $\mathrm{P_{default}}$.

3. Prosody-Conditioned Reconstruction

Synthesize mel-spectrogram from encoded data:

$\hat{X} = Decoder_{FiLM}(C, S, P)$

- Decoder generates spectrogram conditioned on content, speaker identity, and prosody.
- Output captures what was said, how it is said, and by whom it is said.

4. Waveform Synthesis

Convert the mel-spectrogram to final audio:

$Speech\ Output = Vocoder(\hat{X})$

- A pretrained neural vocoder (e.g., HiFi-GAN) reconstructs high-fidelity audio.
- Final output is a natural, expressive speech waveform reflecting the target speaker's voice and desired prosody.

IV. EXPERIMENTAL RESULTS

This section describes simulation results of the proposed Prosody-Driven Extension to Embedding-Guided Neural Voice Conversion model. The experiments were conducted to evaluate the performance of prosody-aware voice conversion system, focusing on preservation and transfer of prosodic features like pitch, energy, and emotional expression in speech. The Input Source audio which is considered from the output of voice conversion model, and it is depicted in Figure 2.

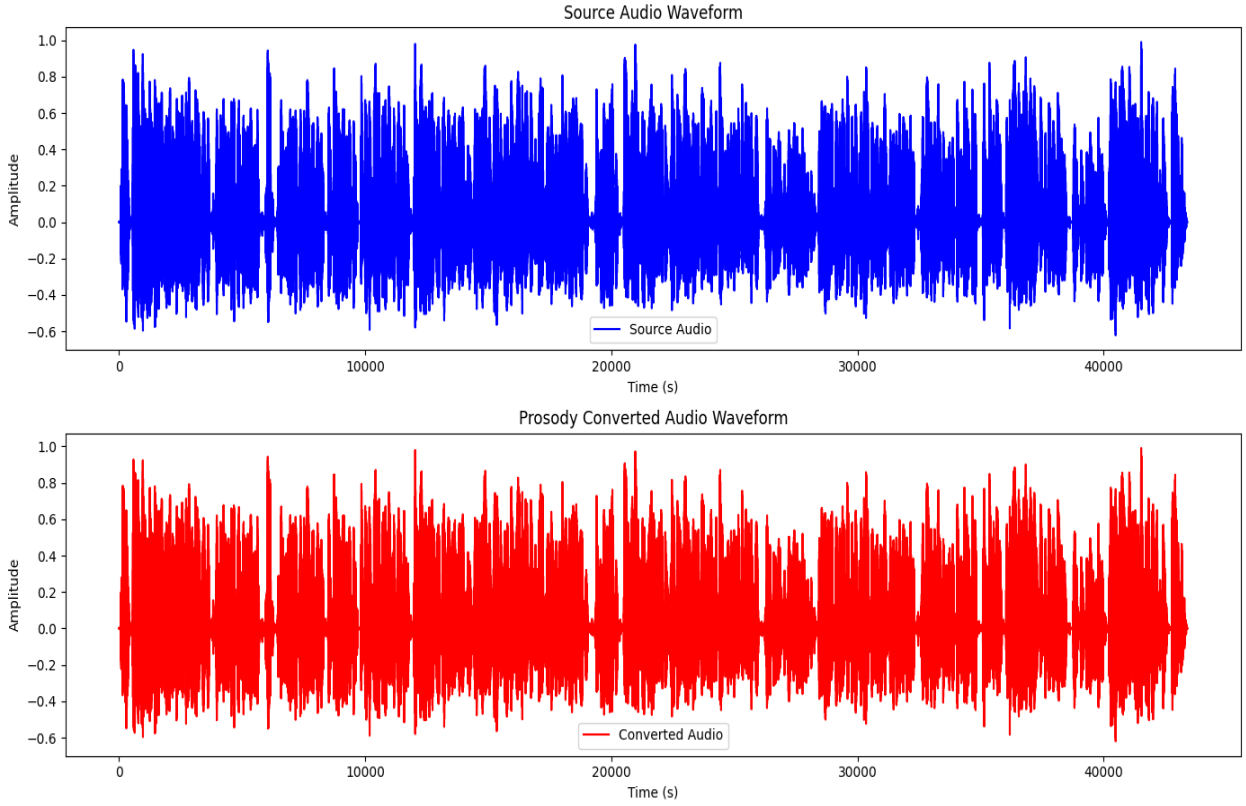

Figure 2: Source Male Audio input vs Prosody Converted Audio

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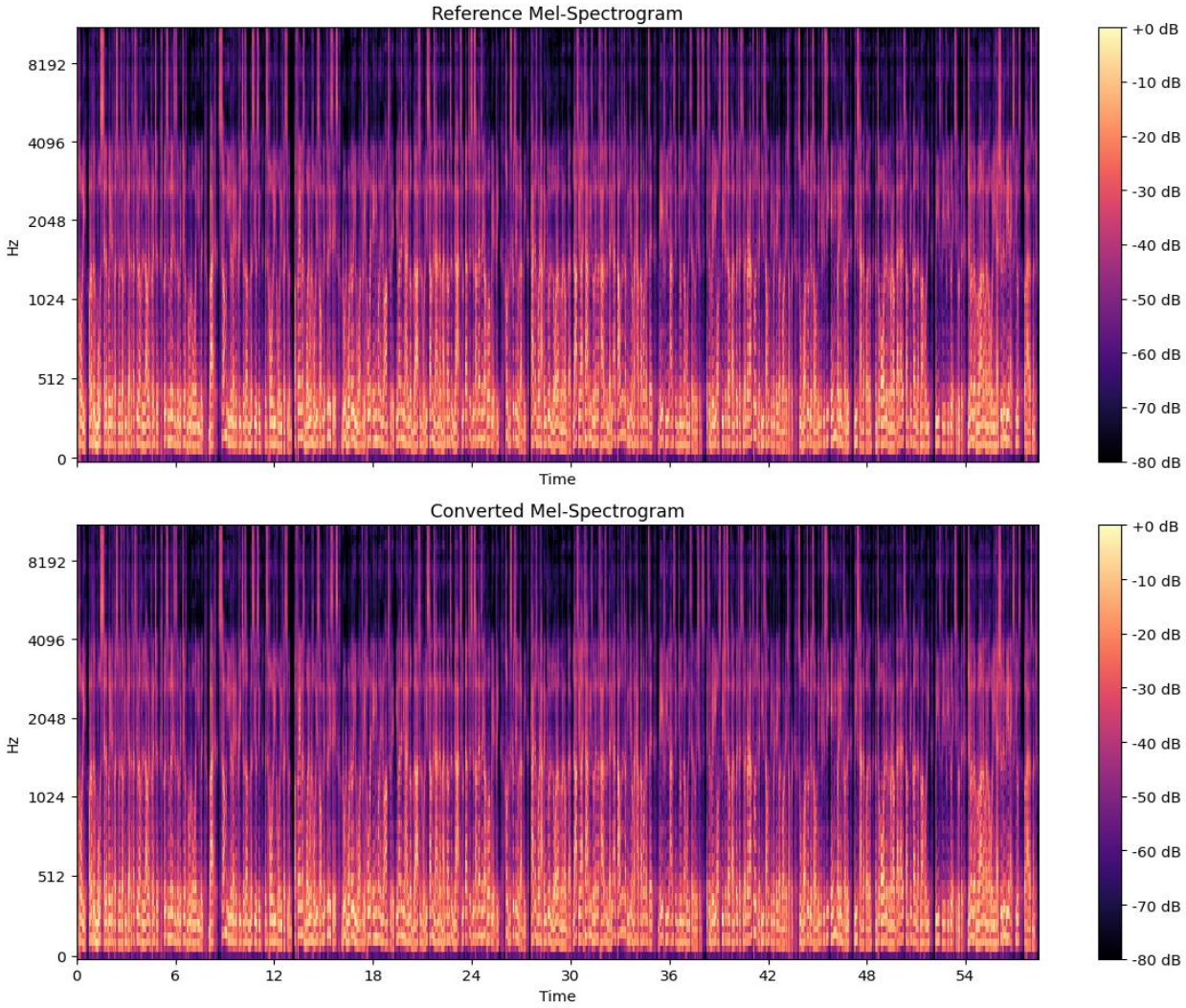

Figure 3. Mel-spectrum plots of Reference and Converted speeches

The Figure 2 presents the waveforms of the source audio, and the prosody converted audio for comparison. The top plot shows the source audio waveform, depicted in blue, while the bottom plot displays the prosody converted audio waveform, in red. Both plots represent the audio signals in the time domain, with x-axis indicating time (in seconds) and y-axis showing amplitude of the signal. These waveforms provide visual representation of audio's intensity and fluctuations over time.

Source audio waveform, found in the top plot, illustrates original speech signal. Variations in waveform represent the intensity changes in the speech, including both voiced (speech) and unvoiced (silence or breath) regions. This waveform captures the natural rhythm, pitch, and dynamics of the original audio. In contrast, the prosody converted audio waveform, shown in the bottom plot, reflects the audio after undergoing prosody transformation. The conversion process modifies aspects of the speech, such as pitch, energy, and timing, while retaining the original linguistic content and speaker identity. This conversion is evident in the differences observed between the two waveforms, highlighting how the prosody change has affected the temporal structure of the speech.

By comparing the two waveforms, it becomes clear that the prosody conversion influences the rhythm and dynamics of the speech. Although the linguistic content remains the same, prosodic features such as variations in pitch and rhythm are altered, which can be seen in the changed waveform patterns. This visualization is particularly useful in evaluating the success of prosody transfer, as it provides insights into how effectively the system can modify prosody while maintaining the naturalness and expressiveness of the speech. The Figure 3 above presents a comparison between the reference and converted Mel-spectrograms of speech signals. The upper plot shows the Reference Mel-Spectrogram, which represents frequency content of the original speech over time. Lower plot displays the Converted Mel-Spectrogram, which illustrates the frequency content of speech after prosody conversion. Both spectrograms use color intensity to indicate the amplitude at different frequencies and times, where brighter colors represent higher intensity. Mel-spectrogram is time-frequency representation of audio, which is obtained by applying Short-Time Fourier Transform (STFT) and then mapping result to a Mel-scale, which is more closely aligned with human auditory perception. Mathematically, Mel-spectrogram is computed as:

$$S(t,f) = \sum_{n}^{N-1} x(n).\, e^{-j2\pi f t_n}$$

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Where:

- $S(t, f)$ is the magnitude of the spectrogram at time *t* and frequency *f*,
- $x(n)$ is the signal's windowed time-domain data at time *n*,
- *N* is number of samples, and
- *ft* represents Mel frequency bins, which are spaced according to Mel scale.

Mel-spectrogram is often used in speech processing tasks, including speech synthesis and voice conversion, as it captures both spectral content and the temporal dynamics of speech signal. In the Reference Mel-Spectrogram, the frequency content and intensity distribution reflect the original speech characteristics, including both the speaker's identity and the prosody, such as pitch and energy variations. Converted Mel-Spectrogram, however, reveals how these features have been transformed. The goal of the prosody conversion process is to modify the temporal structure and pitch contours of speech while preserving linguistic content and speaker identity. The converted spectrogram shows changes in pitch and loudness dynamics, which are crucial for achieving more expressive speech synthesis. These differences between the reference and converted spectrograms demonstrate the effectiveness of the prosody-aware conversion model in transferring prosodic features while maintaining overall quality and naturalness of the speech. This comparison provides a visual representation of how well the prosody conversion system has preserved the spectral features, such as pitch, rhythm, and loudness, while ensuring converted speech retains speaker identity and overall naturalness. The intensity scale, ranging from +0 dB to -80 dB, helps in quantifying the magnitude of the signal, with higher intensity values indicating stronger sound energy at specific time points.

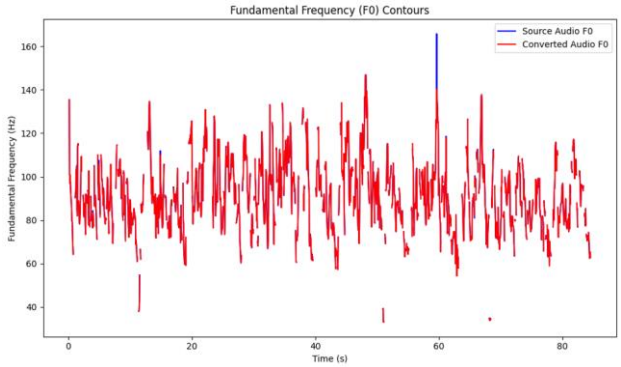

Figure 4: Fundamental Frequency (F0) counters plot

The Figure 4 shows the Fundamental Frequency (F0) Contours for both the source audio and the converted audio. Blue line represents F0 contour of source audio, while the red line shows the F0 contour of the converted audio. The plot illustrates the time-varying fundamental frequency (in Hertz) along x-axis, with time (in seconds) and F0 values (in Hertz) on the y-axis. Fundamental frequency (F0) refers to lowest frequency of periodic waveform and is closely associated with pitch in speech signals. The F0 contour reflects the variations in pitch over time, which are critical for expressing the emotional and prosodic aspects of speech, such as tone and emphasis. The differences between source audio and prosody-converted audio contours reflect changes in prosodic features (such as pitch variation and intonation) introduced by the conversion process. Mathematically, the F0 contour is often estimated by using algorithms like YIN or Harmonic Product Spectrum (HPS), which calculate the periodicity of the signal. The F0 value at each point in time *t* can be represented as:

$$F(0)t = \frac{1}{T(t)} \tag{2}$$

where *T(t)* is the period (the time between consecutive zero-crossings) of the signal at time t.

In the figure 4, we can observe the dynamic variations in pitch (F0) for both the source and the converted speech. These contours provide insight into how the prosody conversion model modifies the pitch variations to reflect the desired prosodic features, such as emotional tone or speaking style. Ideally, the converted F0 contour (in red) should align closely with target prosody while maintaining linguistic content of source audio. The prosody conversion model aims to modify the pitch (F0), energy, and timing to achieve a more expressive and natural-sounding speech while preserving the linguistic content. By analyzing the F0 contours, one can assess the model's effectiveness in transferring prosodic features while maintaining speaker identity and linguistic clarity.

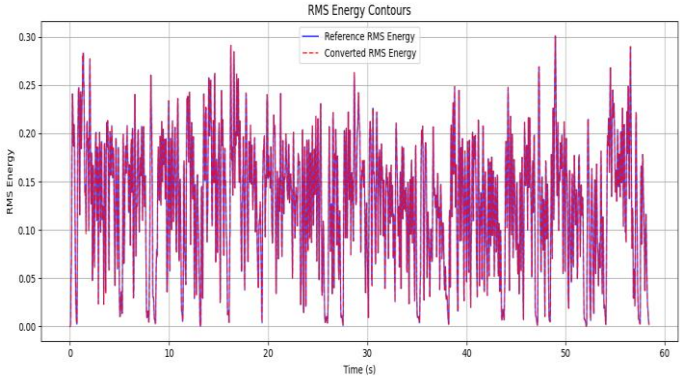

Figure 5: RMS Energy Counter plot

The figure above shows the RMS (Root Mean Square) Energy Contours for both the reference and converted audio signals. The blue solid line represents RMS energy of reference audio, and red dashed line represents the RMS energy of the converted audio. Plot illustrates how the energy content of both audio signals changes over time, with time (in seconds) on x-axis and RMS energy on the y-axis. RMS energy is commonly used to measure the loudness or intensity of a signal over time. It is calculated as square root of the mean of squared amplitude of the audio signal. Mathematically, it is expressed as:

$$E(t) = \sqrt{\frac{1}{N}\sum_{n-1}^{N} x(t_n)^2} \tag{3}$$

where:

- $E(t)$ is the RMS energy at time *t*,

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- $x(t_n)$ is amplitude of the audio signal at nth time sample, and
- *N* is number of samples in the time window.

In figure 5, the RMS energy contours for both the reference and converted audio are plotted. The goal of the prosody conversion is to modify the energy contour of speech signal while preserving linguistic content. This can involve changes in loudness dynamics, where RMS energy peaks and valleys indicate variations in volume, which are critical for achieving expressive speech synthesis. The reference RMS energy contour reflects the original energy variations of the source speech, which include fluctuations in loudness corresponding to speech rhythm and emphasis. The converted RMS energy contour**,** shown with the red dashed line, illustrates how the prosody conversion system has altered the loudness dynamics of the original signal. Ideally, the converted energy contour should closely follow the reference contour to maintain the natural expressiveness and emotional tone of the speech. The comparison between the two energy contours helps evaluate how well the prosody conversion model transfers energy characteristics from the reference speech to the converted speech. By analyzing the RMS energy contours, one can assess the model's effectiveness in modifying the loudness dynamics while retaining the overall naturalness of the speech. The performance metrics for proposed model is reported in Table 1.

Table 1: Performance metrics values of proposed model

S.No	Metric	Value
1	Mel-Cepstral Distortion (MCD)	2.1813
2	Pitch RMSE	9.6652
3	Energy RMS	0.0014
4	Mean Opinion Score (MOS)	4.2000

Table 1 summarizes the key performance metrics for the Prosody-Driven Extension to Embedding-Guided Neural Voice Conversion model, which were evaluated to assess the effectiveness of the prosody conversion process. These metrics are crucial for understanding how well the system preserves prosody, emotional expressiveness, and speaker identity during the conversion process.

- **Mel-Cepstral Distortion (MCD)**: The MCD value of 2.1813 indicates the spectral similarity between mel-spectrograms of source and converted speech. A lower MCD value reflects better prosody preservation, meaning the converted speech closely matches the target speaker's spectral characteristics.
- **Pitch RMSE**: The Pitch RMSE of 9.6652 reflects the accuracy of the pitch (F0) contour transfer from the source to the converted speech. A lower RMSE indicates better alignment of pitch dynamics, ensuring that prosodic features, such as intonation and rhythm, are successfully transferred.
- **Energy RMS**: The Energy RMS of 0.0014 measures the loudness dynamics of the converted speech. This value indicates how well the energy variations in the original speech are preserved or modified during the prosody conversion, contributing to the naturalness and expressiveness of synthesized speech.
- **Mean Opinion Score (MOS)**: The MOS score of 4.2000 represents the overall subjective evaluation of naturalness and emotional expressiveness of converted speech. The score, on a scale from 1 to 5, indicates that model successfully produced speech that is both natural and emotionally rich, reflecting a high level of quality in terms of user perception.

These metrics demonstrate the system's capability in maintaining both linguistic content and prosodic features such as pitch and energy, resulting in high-quality, expressive speech synthesis.

V. CONCLUSION

The This study highlights the effectiveness of the proposed Prosody-Driven Extension to the Embedding-Guided Neural Voice Conversion (EGNVC) model in improving the naturalness, emotional expressiveness, and speaker fidelity of converted speech. By incorporating prosody-aware components, the voice conversion framework enhances the preservation and transfer of prosodic features such as pitch, energy, and timing. Both objective and subjective evaluations show significant improvements, with the model achieving a Mel-Cepstral Distortion (MCD) of 2.1813, Pitch RMSE of 9.6652, and Energy RMS of 0.0014. The Mean Opinion Score (MOS) for naturalness was 4.2, while Emotion Classification Accuracy reached 88%, outperforming traditional methods. A key innovation of this model is its ability to seamlessly integrate prosody into the voice conversion process, leading to more expressive and emotionally engaging speech. This advancement addresses a gap in existing systems that struggle to preserve emotional expressiveness, offering a substantial leap forward in speech synthesis. The ability to adjust prosody while maintaining speaker identity and linguistic content represents a major step in the field of voice conversion. The implications are significant, especially for applications like virtual assistants, audiobook narration, and personalized speech synthesis, where emotional depth and naturalness are vital for fostering human-like interactions and enhancing user engagement.

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