

# Improving the expressiveness of TTS synthesis with non-autoregressive neural vocoding

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## 1. Research Question

Why are expressive speech important in delivering messages?

- conveys meaning, tone, and emotion.
- adds nonverbal cues that build connection and engagement.
- clarifies key points and highlights important ideas.
- captures attention and keeps listeners involved.

## 2. Problem Formulation

Flexible and appropriate rendering of expressivity in a synthetic voice is still out of reach:

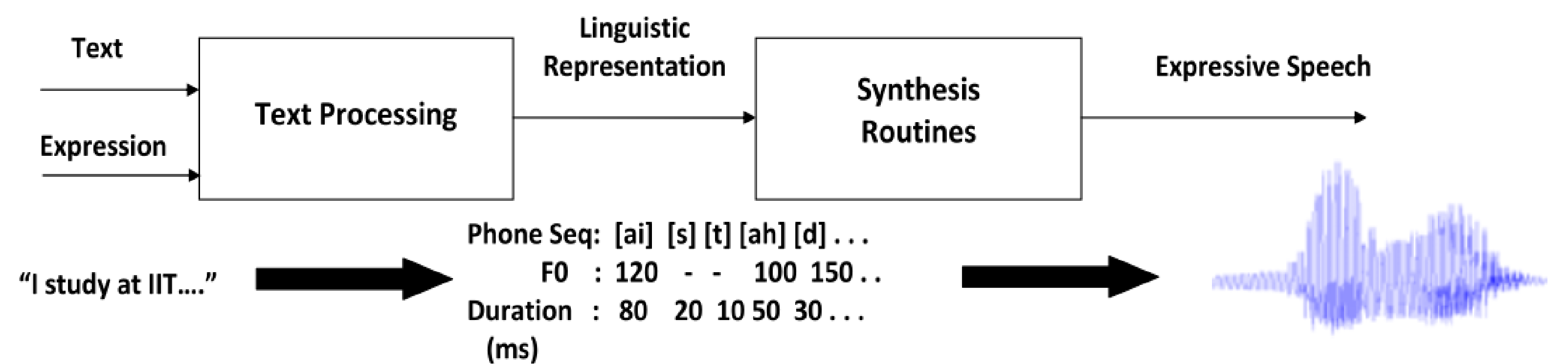
- making a voice sound happy or subdued, friendly or empathic, authoritative or uncertain is beyond what can be done today.

## 3. Goals

- Increase the flexibility in expression while maintaining the quality of state-of-the-art systems

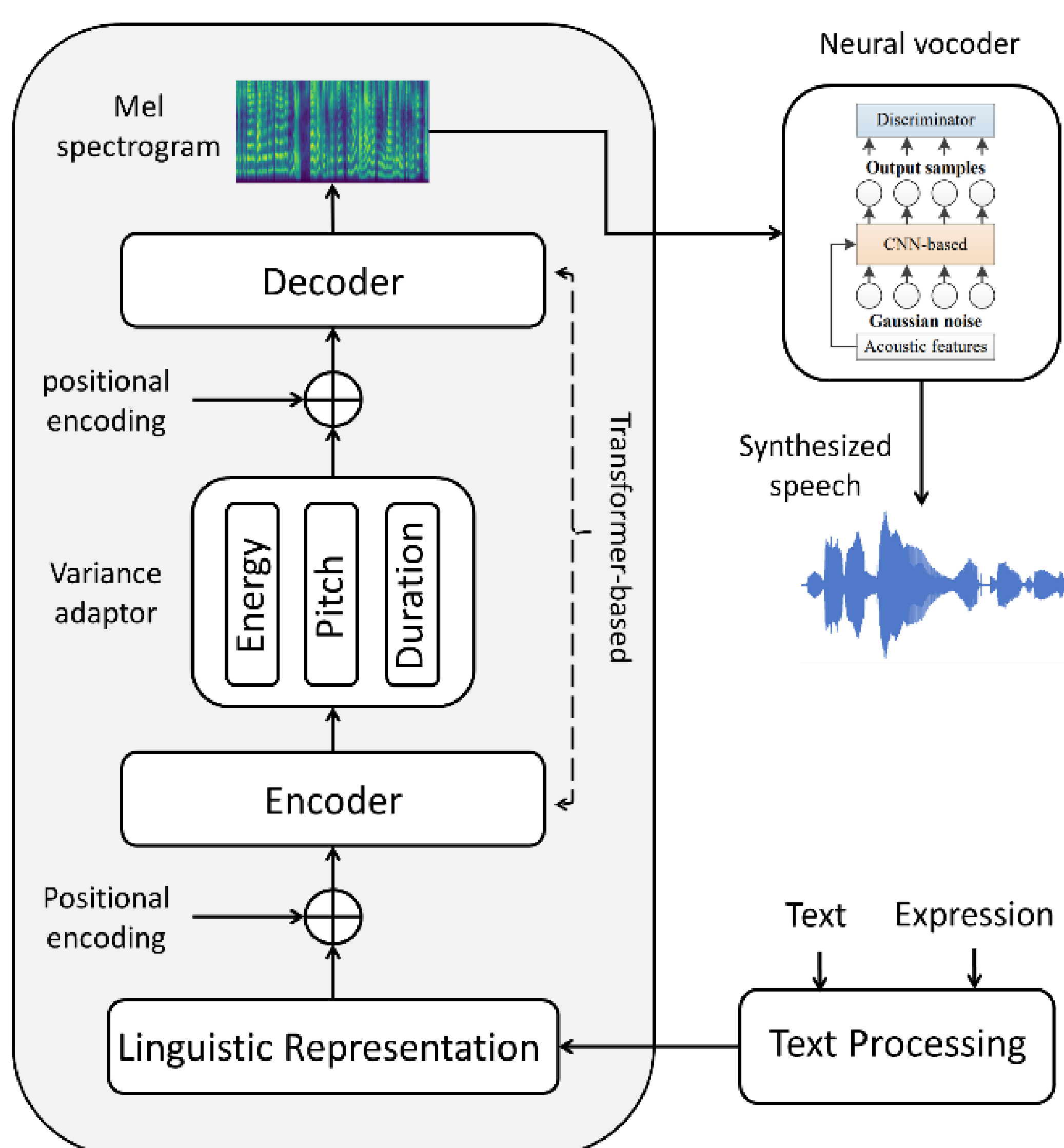
## 4. Expressive Speech Synthesis

- In **linguistics**, expressivity may change the choice of words or syntactic structures.
- In **acoustics**, it impacts various characteristics like energy, pitch, duration, etc.



## 5. Methods

- Propose a high-quality and expressive multi-speaker TTS model, which can flexibly synthesize speech with the style extracted from a target speaker.
- Used a non-autoregressive Mel-spectrogram prediction model (i.e., FastSpeech2), which has demonstrated improved speed and robustness compared to traditional autoregressive models.



## 6. Experimental conditions

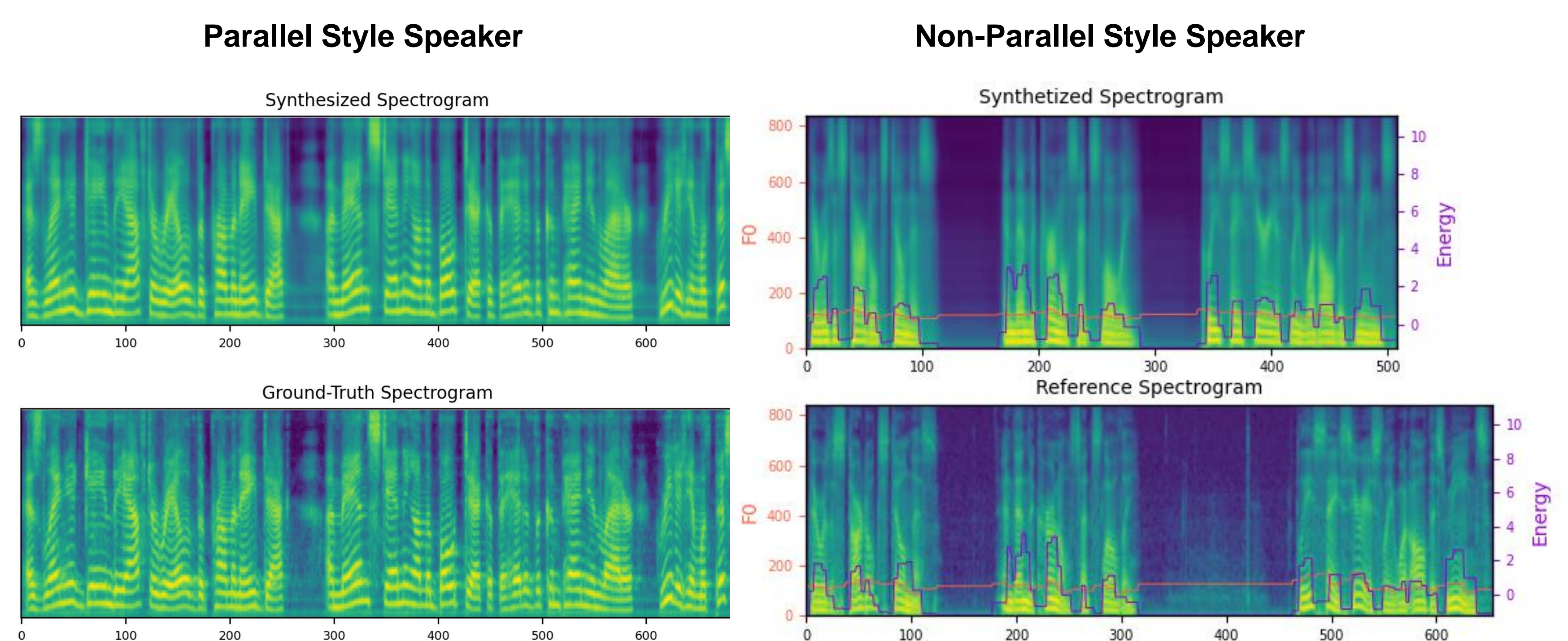
### Datasets

- LibriTTS dataset contains 110 hours speech with 1151 reading-style speakers. We convert the speech sampling rate to 16KHz.
- use 12.5ms hop size, 50ms window size to extract mel-spectrogram.
- convert text into phoneme using grapheme-to-phoneme conversion and take phoneme as the encoder input.

### Model

- 4 FFT blocks on both phoneme encoder and mel-spectrogram decoder following FastSpeech2.
- The architecture of pitch, energy and duration predictor in the variance adaptor are the same as those of FastSpeech2.
- The phoneme discriminator consist of fully connected layers.

## 7. Results



Loss	Training	Validation
Mel Loss	0.5752	0.6324
Pitch Loss	0.1455	0.2545
Energy Loss	0.1719	0.2076
Duration Loss	0.0867	0.0987
Total Loss	0.9792	1.1933

- Figures show the example of generated speech from the reference speaker.
- We observe that our model generates high quality mel-spectrogram which is comparable to ground-truth mel-spectrogram.
- Based on the losses, model is performing well on the training and validation data.

## 8. Conclusion and Future work

- Propose an expressive TTS model to generate various styles of speech of multiple speakers.
- Confirmed through experiments that our model synthesize high-quality spectrogram given the reference audios from both parallel and non-parallel speakers.
- We will evaluate subjective naturalness of synthesized speech
- We will extend the TTS model to more languages and Enable multi-lingual speech style transfer

## 9. Acknowledgment

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## References

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