

Tacotron-based acoustic model using phoneme alignment for practical neural text-to-speech systems

Takuma Okamoto¹, Tomoki Toda^{2,1}, Yoshinori Shiga¹, and Hisashi Kawai¹ ¹National Institute of Information and Communications Technology, Japan, ²Nagoya University, Japan





Phoneme duration

1. Introduction

Conventional text-to-speech (TTS) systems

- Duration and acoustic pipeline models with source-filter vocoders
 - Widely used in practical systems but not high quality synthesis

End-to-end neural TTS systems

- Sequence-to-sequence (seq2seq) model with neural vocoders
 - # Jointly optimizing duration and acoustic models and <u>directly converting character</u> or phoneme sequences to acoustic features (mel-spectrogram)
- State-of-the art end-to-end TTS models
 - # Tacotron 2 with autoregressive WaveNet vocoder: <u>Human guality synthesis</u>
 - ClariNet (Deep voice 3 + parallel WaveNet): Entire end-to-end real-time neural TTS
 - Transformer-based TTS: <u>Faster training than Tacotron 2</u>

Problem of seq2seq models due to attention prediction error

- Speech samples sometimes cannot be successfully synthesized
- * Crucial problem for practical TTS systems

Real-time, high-fidelity, and stable neutral TTS systems with Tacotron structure

- Introducing conventional duration models to sophisticated seg2seg acoustic models
 - * HMM-based forced alignment can be relatively easily obtained
 - * Conventional duration model can estimate almost accurately predict phoneme durations

2. Seg2seg acoustic model with full-context label input

Tacotron 2 with full-context label input for pitch accent languages

- Input: Full-context label (130 dims)
- Output: Mel-spectrogram (80 dims)

Real-time neural TTS with WaveGlow vocoder

Real time factor (RTF) with a GPU: 0.16



Input text Text analyzer	Tacotron encoder 1 × 1 conv layer Agents 1 × 1 conv LSTM)
Full-context label (Phoneme-level)	Location sensitive attention	1)
	2 layer pre-net 2 LSTM layers	
Acoustic features (Frame-level)	5 conv layer post-net projection Linear projection	ear ction
	Neural vocoder	toke:
		10

T. Okamoto *et al.*, Interspeech 2019

This model is also unstable due to attention-based seg2seg structure

3. Proposed method Full-context label Full-context label Phoneme duration (Phon eme-level) Full-context label Phoneme duration (Phoneme-level)



Tacotron with forced attention (FAT)

(Phone

- Encoded features are duplicated and redundant for decoder
 - # FAT cannot outperform Tacotron (Y. Yasuda et al., ICASSP 2019)

Proposed acoustic model with Tacotron decoder and phoneme duration (PAM)

- HMM-based forced alignment and bidirectional LSTM-based duration model
- Acoustic model with bidirectional LSTM and decoder of Tacotron 2
 - Redundancy in FAT can be reduced

4. Experiments with WaveGlow vocoder

- Simulation condition
 - Japanese Female corpus: 18 h
 - Acoustic features
 - Mel-spectrogram: 80 dims, 12.5 ms
 - * Vocoder features (fo, vuv, mel-cepstrum): 1 + 1 + 35 = 37 dims. 5 ms





Results



RTF with an NVIDIA Tesla V100

Method	AM RTF	Total RTF
(A):WG-MELSPC-AS	-	0.066
(B):WG-MELSPC-TTS-seq2seq	0.063	0.13
(C):WG-MELSPC-TTS-CAM	0.015	0.08
(D):WG-MELSPC-TTS-CAM (OD)	0.015	0.08
(E): WG-MELSPC-TTS-FAT	0.049	0.12
(F):WG-MELSPC-TTS-FAT (OD)	0.049	0.12
(G):WG-MELSPC-TTS-PAM	0.061	0.13
(H):WG-MELSPC-TTS-PAM (OD)	0.061	0.13
(I):WG-VF-AS	-	0.06
(J):WG-VF-TTS-CAM	0.045	0.10
(K):WG-VF-TTS-PAM	0.138	0.20
(L):WN-VF-AS	-	200
(M):WN-VF-TTS-PAM	0.06	200

Real-time, high-fidelity, and stable neural TTS can be realized by PAM