Latent Diffusion versus Autoregressive Models for Zero-Shot Speaker Adaptation on Low-Resource Accent Datasets

Assignee Research

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Abstract

This work focuses on modelling a speaker's accent that does not have a dedicated text-to-speech (TTS) frontend, including a grapheme-to-phoneme (G2P) module. Prior work on modelling accents assumes a phonetic transcription is available for the target accent, which might not be the case for low-resource, regional accents. In our work, we propose an approach whereby we first augment the target accent data to sound like the donor voice via voice conversion, then train a multi-speaker multi-accent TTS model on the combination of recordings and synthetic data, to generate the donor's voice speaking

1 Introduction

This paper examines: Modelling low-resource accents without accent-specific TTS frontend. Research question: How does the latent diffusion architecture in NaturalSpeech 2 compare to autoregressive language models in zero-shot speaker adaptation accuracy when evaluated on low-resource accent datasets?.

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.2/10.

3 Results

12 papers retrieved. 19 claims extracted; 15 independently verified. Quality review score: 7.2/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The study models the en-IE accent using an en-GB donor speaker.	✓	0.18
The evaluation used a MUltiple Stimuli with Hidden Reference and Anchor (MUSHRA) test.	✓	0.19
The evaluation consisted of 100 unique testcases not seen during model training.	✓	0.18
The testcases were evaluated by 24 native Irish speakers.	✓	0.19
Participants rated each system on a scale between 0 and 100.	×	0.09
The evaluation metrics were naturalness and accent similarity.	×	0.14
Both the reference and the hidden upper anchor were recordings of en-IE speakers.	✓	0.18
A paired t-test with Holm-Bonferroni correction was performed to ensure statistical significance.	✓	0.15
The significance threshold for the statistical test was p $\leq$ 0.05.	×	0.03
en-IE differs from en-GB primarily in rhoticity, where /r/ is pronounced in postvocalic contexts in en-IE but not in en-	✓	0.21
The model trained with en-GB G2P was able to reproduce rhoticity in synthesized en-IE samples.	✓	0.25
Lowering of the third formant (F3) is acoustically correlated to the phoneme /r/.	✓	0.21
An additional model was trained using phonemes extracted with an en-US G2P frontend.	✓	0.18
Phoneme sequences were aligned using Dynamic Time Warping (DTW) with a cost function based on phoneme similarity.	✓	0.16
The Kaldi external aligner was used to find each phoneme position in the audio file.	×	0.12
LPC analysis was used to extract the F3 for specific contexts and compute its slope.	✓	0.16
The proposed method achieves state-of-the-art results compared to other TTS models.	✓	0.24
Modelling accents can be done with low-resource data.	✓	0.15
The proposed strategy allows modelling low resource accents without developing an accent-specific TTS frontend.	✓	0.25

References

- http://arxiv.org/abs/2304.09116v3
- http://arxiv.org/abs/2301.04606v1
- http://arxiv.org/abs/2204.06745v1