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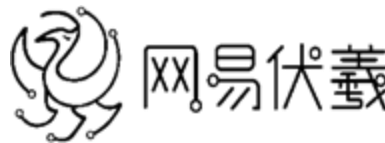


# MacST: Multi-Accent Speech Synthesis via Text Transliteration for Accent Conversion

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# Introduction

- **Foreign Accent Conversion:** Convert the accent of the source speech
    - While keeping the linguistic content and the speaker identity.
  - **Problem:** Lack of parallel dataset with only accent changes.
  - **Solution:** To generate the target samples to build synthetic parallel dataset.
    - However, it can lead some problems.
      - Entanglement issue of speaker and accent
      - Limited availability of accented speeches.
- We propose a pipeline to address these issues using **text transliteration**.

# Proposed System

- MacST: Multi-accent speech synthesis via text transliteration to construct parallel accent dataset
  - **Translation:** Converting the language while keeping the similar meaning.
  - **Transliteration:** Converting the language while keeping the phonetic similarity.
- Procedure:
  - Describe English sentences using the characters of the target language (**transliteration**).
    - E.g. *I love you* → आई लव यू (aaee lav yoo) or アイラブユー (ai rabu yū)
  - Use **Multilingual TTS** to generate the accented speech from transliterated texts.

American



Hindi



Korean



Japanese



*"Again he had done the big thing."*

# Hypothesis and Motivation

- **Hypothesis:**

- Lexical features of accents are based on availability of phonemes in the native languages [1-2].
- Large Language Models (LLMs) is capable of transliterating texts of target languages.

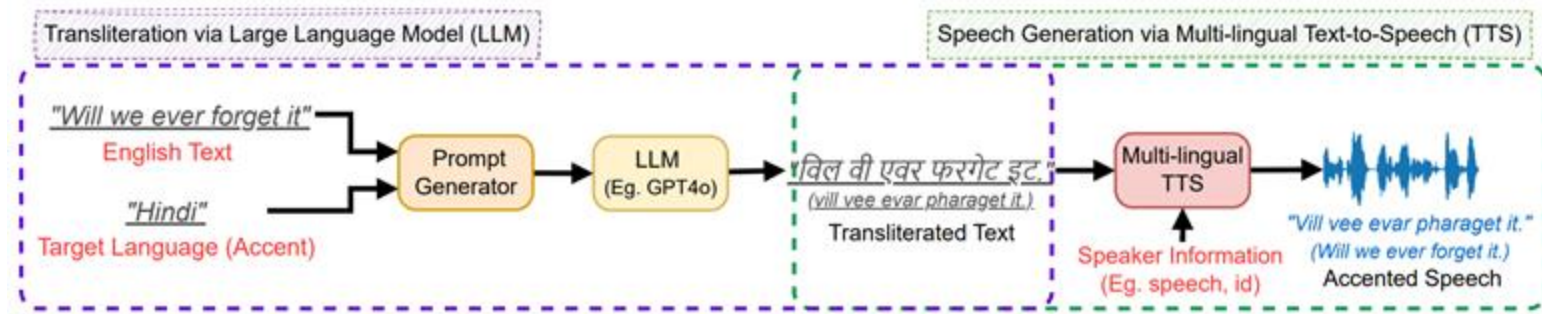
- **Motivation:**

- We do not need accented speech samples.
- We can avoid entanglement of speaker and accent.
- MacST applies to *any* English texts and *any* speaker.
- Consistent linguistic representation in accented speech across different speakers.

[1] Alison Behrman: Segmental and prosodic approaches to accent management

[2] James Flege: Second language speech learning: Theory, findings and problems

# Methodology



- Two Procedures:
  - Text Transliteration via Large Language Models (LLMs)
  - Speech Generation via Multilingual Text-to-Speech (TTS) Models
- Three inputs: English Text, Target Accent, and Speaker Information
- Speaker Information depends on TTS models.
  - In this paper, speech samples from the chosen speaker.
- This system can be applied to various LLMs and Multilingual TTS models.

# Dataset Analysis (Experiment Setup)

- **Target Accents:** American, Hindi, and Korean
- We synthesize accented speech samples using native and non-native speakers.
  - Native Speaker: Accent Addition
  - Non-native Speaker: Accent Enhancement
- **Evaluation Metrics:** MUSHRA tests for Speech Naturalness (Humanness) and Accentedness
- **Comparing Datasets:** L2-ARCTIC and CMU-ARCTIC
  - ARCTIC datasets contain speech samples from different speakers with the same transcripts.
    - *Each speaker only speaks in a single accent.*

# Dataset Analysis (Results)

- **American Speakers:** SLT
- **Hindi Speakers:** ASI, TNI
- **Korean Speakers:** HKK, YDCK
- **MacST:** Proposed system
- The language in MacST indicates the transliteration language.
- Accent Addition Capability is good.
  - E.g. SLT/American → SLT/Hindi
- Accent Enhancement Capability is also good.
  - Ground-Truth → MacST for ASI/Hindi, TNI/Hindi, HKK/Korean, and YDCK/Korean

	Naturalness (↑)	Accentedness (↑)
Ground-Truth (SLT/American)	76.48 ± 3.82	9.56 ± 1.32
MacST (SLT/American)	70.95 ± 4.07	10.78 ± 1.41
Ground-Truth (ASI/Hindi)	85.17 ± 1.87	67.67 ± 2.60
Ground-Truth (TNI/Hindi)	81.29 ± 2.76	70.74 ± 2.40
MacST (SLT/Hindi)	69.51 ± 3.99	51.61 ± 3.02
MacST (ASI/Hindi)	82.12 ± 2.36	73.61 ± 2.51
MacST (TNI/Hindi)	79.64 ± 2.82	77.35 ± 2.66
Ground-Truth (SLT/American)	66.84 ± 3.45	6.90 ± 1.07
MacST (SLT/American)	70.37 ± 3.52	8.56 ± 1.40
Ground-Truth (HKK/Korean)	75.28 ± 2.55	39.08 ± 2.46
Ground-Truth (YDCK/Korean)	78.84 ± 1.87	32.90 ± 2.10
MacST (SLT/Korean)	58.47 ± 4.85	77.63 ± 2.33
MacST (HKK/Korean)	63.22 ± 4.06	83.40 ± 1.67
MacST (YDCK/Korean)	63.87 ± 4.36	83.44 ± 1.67

# Accent Conversion (Experiment Setup)

- **Accent Conversion:** American  $\rightarrow$  Hindi
- We synthesize accented speech samples using American speaker (SLT).
- **Evaluation Metrics:**
  - MUSHRA tests for Speech Naturalness (Humanness) and Accentedness
  - Objective Evaluations:
    - Speech Intelligibility: Word Error Rate (WER)
    - Speaker Similarity: Speaker Encoding Cosine Similarity (SECS)
    - Accentedness: Accent classification prob (Hindi)
- **Two accent conversion models with different training datasets:**
  - The parallel dataset with the ground-truth source and the synthetic target (1 hour pairs)
  - Additional pairs of the synthetic source and the target (additional 4 hours): **Data Augmentation**



# Accent Conversion (AC) (Results)

	Speech Quality		Accentedness			Speaker Similarity
	MUSHRA ( $\uparrow$ )	WER ( $\downarrow$ )	MUSHRA ( $\uparrow$ )	Classification Prob. ( $\uparrow$ )	AECS Diff. ( $\uparrow$ )	SECS ( $\uparrow$ )
Ground-Truth (American)	$76.48 \pm 3.82$	1.97	$9.56 \pm 1.32$	0.000	-	-
MacST (American)	$70.95 \pm 4.07$	1.75	$10.78 \pm 1.41$	0.000	-	0.866
MacST (Hindi)	$69.51 \pm 3.99$	8.52	$51.61 \pm 3.02$	0.819	-	0.822
AC w/o Data Augmentation	$51.48 \pm 3.73$	13.99	$34.85 \pm 2.29$	0.801	0.411	<b>0.834</b>
AC w/ Data Augmentation (ours)	<b><math>67.18 \pm 3.43</math></b>	<b>8.74</b>	<b><math>47.26 \pm 2.65</math></b>	<b>0.897</b>	<b>0.465</b>	0.833

- Consistent speaker characteristics between the source and the converted audio.
- Accent conversion significantly increased accentedness: Ground-Truth (American)  $\rightarrow$  AC results
- Data Augmentation enhanced the conversion results in speech quality and accentedness.

# Conclusion

- We introduce the multi-accent speech synthesis via text transliteration method (MacST)
  - Transliteration via LLMs
  - Speech Generation via Multilingual TTS Models
- Dataset analysis validates MacST's ability to amplify accents in native and non-native English speakers.
- Experiment results validate the efficacy of our method in training accent conversion models.



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Q & A

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# Accent Conversion (Model Configuration)

- **Accent Conversion (AC):** Voice Transformer Networks (VTN)
  - A sequence-to-sequence encoder-decoder model.
  - Mel-spectrogram as input and output.
  - We pretrain AC with TTS-like tasks using LibriTTS-R.
- **Pre-training Strategy:** Two-stage pretraining.
  - 1st stage: Input is Hubert discrete tokens (without repetition) and Output is Mel-spectrogram
  - 2nd stage: Input and Output are Mel-spectrograms
    - Initialize encoder and Freeze decoder
- **Vocoder:** HiFiGAN trained on LibriTTS-R and ARCTIC datasets.

# Text Transliteration with LLMs

- **How to build a prompt for LLMs**

- Word-level transliteration with phoneme-sequence.
- Put three candidate words and Sort them in similarity order.
- We include few transliterated samples to avoid *translation*.

- **Post Process**

- We got six responses in total, three for GPT 3.5 Turbo and three for GPT-4o.
- Among six responses, we obtain the most frequent transliterated texts for each word.
- We re-put commas and periods.

# Speech Generation with Multilingual TTS

- **Multilingual TTS Models:** the Eleven Multilingual v2 model from [11Elevenlabs](#).
  - It covers 29 languages.
  - Speaker Condition: speech samples (voice clone)
  - Language Condition: the characters of the input text

# Evaluation Metrics (Accentedness)

- We used three metrics to evaluate “Accentedness” of synthesized speeches.
  - MUSHRA test for Accentedness (strength of the accent)
  - Classification probability for Hindi accent using a pre-trained accent classification model.
  - Accent Encoding Cosine Similarity (AECS) Difference.
- **AECS Difference:** To quantify accent similarity of converted speech from native and non-native speech.
  - Obtain accent embeddings of converted sample and MacST samples of American and Hindi speech.
  - Calculate AECS between
    - Converted speech and American speech: AECS\_american
    - Converted speech and Hindi speech: AECS\_hindi
  - compute “AECS\_hindi - AECS\_american”



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