CCA-MDD: A COUPLED CROSS-ATTENTION BASED FRAMEWORK FOR STREAMING MISPRONUNCIATION DETECTION AND DIAGNOSIS

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ABSTRACT

End-to-end models are becoming popular approaches for mispronunciation detection and diagnosis (MDD). A streaming MDD framework is demanded by many practical applications still remains a challenge. This paper proposes a streaming end-to-end MDD framework called CCA-MDD. CCA-MDD supports online processing and is able to run strictly in real-time. The encoder of CCA-MDD consists of a conv-Transformer network based streaming acoustic encoder and an improved cross-attention named coupled cross-attention (CCA). The coupled cross-attention integrates encoded acoustic features with pre-encoded linguistic features. An ensemble of decoders trained from multi-task learning is applied for final MDD decision. Experiments on publicly available corpora demonstrate that CCA-MDD achieves comparable performance to published offline end-to-end MDD models.

Index Terms— mispronunciation detection and diagnosis, coupled cross-attention, streaming end-to-end model

1. INTRODUCTION

Mispronunciation detection and diagnosis (MDD) is a necessary component in computer-assisted pronunciation training (CAPT) systems [1]. The MDD problem is an active research topic. Traditional MDD approaches consist of goodness-of- pronunciation (GOP) [2][3] based and automatic speech recognition (ASR) based [4][5] components. The emergence of end-to-end (e2e) neural networks promises potential performance improvement, leading to new research interests in e2e MDD models [6][7][14]. The different MDD frameworks are illustrated in Fig. 1.

End-to-end MDD models allow integrated modeling of text prompts and acoustic signals with advanced deep neural networks. End-to-end MDD modeling alleviates the need for building a long pipeline as in traditional approaches. The pipeline usually consists of multiple steps such as forced-alignment and phonological rule matching. These steps are prone to error accumulation, leading to inferior MDD performance.

A common practice of e2e MDD is to combine the models of the original pipeline, which are typically an acoustic model and a label classifier, into a unified model. For example, the e2e MDD model in [11] consists of a convolution neural network and recurrent neural network (CNN-RNN) as acoustic encoder and a connectionist temporal classification (CTC) [12] decoder that takes the encoded acoustic features and text information to detect mispronunciation. Recent studies suggest that injecting text information during acoustic modeling improves MDD performance [7][8][10][13]. The integrated modeling of text and acoustic modalities helps to learn inherent text-acoustic mapping. SED-MDD [10] encodes linguistic features with a sentence encoder and feeds the encoded linguistic cues to acoustic model through an attention for further context modeling. The model in [7] is Transformer based. The model consists of multi-head attention (MHA) to combine the encoded linguistic and acoustic information and capture the corresponding mappings. Self-training methods which learn context representation from unlabeled data are explored in [4][15].

In this work, we aim to construct a streaming e2e MDD framework as illustrated in Fig. 1(d). A streaming MDD framework is useful to many real-time applications. For example, in an interactive CAPT system [16], users would expect the system to return MDD feedback immediately once users recorded their speech. When the speech is long, users may expect the system to output partial MDD result simultaneously before the user finishing the whole speech. An interactive CAPT system requires an MDD model to support online decoding and retain high MDD performance. Existing e2e MDD solutions hardly satisfy this requirement due to the difficulty in modeling text and acoustic features in a streaming manner, especially with attention mechanism. We are motivated by the success of streaming ASR [17][19]. We apply a streaming ASR acoustic encoder based on conv-Transformer blocks [18] for processing input acoustic frames. To capture integrated text-acoustic features in a streamable manner, we propose coupled cross-attention (CCA) mechanism which considers alignment between text and acoustic dimensions. This attention mechanism allows flexible alignment and handles mismatches.

Fig. 1. Different MDD frameworks. (a) GOP based, (b) ASR based, (c) end-to-end model based, and (d) our streaming framework.
between input text prompt and pronunciation in recorded speech which occurs in MDD problem. We further apply multi-task learning to simultaneously model phoneme prediction and pronunciation error state, and an ensemble mechanism for final MDD decision.

This paper is organized as follows. We first describe our proposed CCA-MDD in the next section. We present the experimental setup and evaluation results in Section 3. Finally we conclude this work in Section 4.

2. PROPOSED METHOD

As shown in Fig. 2, CCA-MDD consists of two key components, an incremental feature encoder and an ensemble-augmented decoder.

2.1. Incremental Feature Encoder (IFE)

The incremental feature encoder (IFE) contains three sub-encoders, i.e., incremental acoustic encoder (IAE), reference encoder (RE), and joint encoder (JE). Joint encoder jointly encodes linguistic and acoustic embedding from IAE and RE.

Motivated by the success of Conv-Transformer Transducer (ConvTT) [18] for streaming ASR, we borrow the acoustic encoder in ConvTT to implement our IAE. Specifically, we build the IAE with two conv-Transformer blocks and adopt the same parameter setting as in [18] for these blocks. Note that our sub-sampling rate of speech frames is 40ms with 2 blocks instead of 80ms as in [18] with 3 blocks. Benefited from these carefully-designed interleaved Transformer layers and convolution layers, the IAE encodes acoustic frames in a streaming manner. When processing a speech utterance, conv-Transformer blocks only require a small look-ahead window (additional 60ms latency for CCA-MDD with 2 blocks) for modeling future context, instead of the whole utterance.

Reference encoder takes reference phonemes converted from the reference text prompt according to a dictionary as input and transforms each phoneme into N-dimensional (N = 384 in this paper) linguistic feature vector. We construct the RE with a network of two Transformer layers with full attention. The JE consists of an improved cross-attention named coupled cross-attention (CCA), and a Transformer based post-net module. As shown in Fig. 3, CCA is composed of two multi-head cross-attention modules as follows:

\[
\text{score}_h = \text{softmax}(\frac{W^Q_h f_i(W^K_h d)^T}{\sqrt{m}})
\]

\[
\text{attention}^f_h = \text{score}_h \cdot (W^K_h d)
\]

\[
g_{\text{MHA}} = \text{concat}_{h \in H} (\text{attention}^f_h) W^Q_f
\]

\[
\text{attention}^d_h = (W^K_h f) \cdot \text{score}_h^T
\]

\[
s_{\text{MHA}} = \text{concat}_{h \in H} (\text{attention}^d_h) W^Q_d
\]

where \(K, Q, V\) are dimensions of key, query, and value respectively. The index of attention heads is denoted as \(h\) with a total number of \(H\) heads. The matrices \(W^K_h\) and \(W^Q_h\) are the weights for encoded acoustic feature vector \(f_i\) at frame index \(i\) and all the available acoustic feature vectors \(f\) respectively. The matrices \(W^K_h\) and \(W^Q_h\) are projection matrices of linguistic feature vector \(d\) of reference phonemes. The number of reference phonemes is denoted by \(m\). The matrices \(W^K_f\) and \(W^Q_f\) are the output weights of upper attention and lower attention respectively with \(O\) as the output dimension. The concatenation operator is denoted as \(\text{concat}(\cdot)\).

The upper attention \(\text{attention}_h^f\) supports mapping of currently encoded acoustic feature vectors to encoded linguistic output \(d\) from the RE. The bottom attention \(\text{attention}_h^d\) is expected to build mappings from linguistic features to acoustic features. These two attentions are conditioned on the same matching score \(\text{score}_h\). The score \(\text{score}_h\) is computed online with currently processed acoustic frames. The upper attention output \(g_{\text{MHA}}\) is computed immediately as the whole linguistic context \(d\) is known as prior information. The bottom attention output \(s_{\text{MHA}}\) is computed with full acoustic context \(f\) of entire utterance. The on-the-fly generation of \(g_{\text{MHA}}\) allows online frame-wise pronunciation recognition. The full-context dependent output \(s_{\text{MHA}}\) performs the final sentence-based mispronunciation diagnosis. The post-net is constructed with one-layer Transformer that takes only \(g_{\text{MHA}}\) as input.

2.2. Ensemble-augmented Decoder (EAD)

The ensemble-augmented decoder (EAD) consists of three parts, CTC decoder, phoneme classifier and error state classifier. The parameters are learnt with a multi-task learning mechanism. The CTC decoder is constructed with one-layer fully connected feed-forward network of 512 hidden units. Similar to decoder in ASR, the online decoder predicts phoneme labels from outputs of the post-net.

Both the phoneme classifier and the error state classifier take the attention output \(s_{\text{MHA}}\) from the JE as input. The two classifiers are used to predict phoneme labels and error states respectively. The error state of a phoneme label tells whether the phoneme is pronounced correctly against the reference phoneme sequence. The lengths of the outputs of the two classifiers are consistent with the length of the reference phoneme sequence. We build these two classifiers with the same model structure, which consists of a stack of two Transformer layers followed a multi-layer perception (MLP). The error state classifier further takes the intermediate representation which is the output of the second Transformer of the phoneme classifier as a condition additional to \(s_{\text{MHA}}\). The intermediate representation is discriminative and contributes to improvement of error state classification. Since \(s_{\text{MHA}}\) is fully context-dependent, these two classifiers do not support online output. The two classifiers require the whole
input sequence for their predictions.

We train the three decoders with multi-task learning, and compute CTC loss $L_{CTC}$, cross-entropy loss $L_{PH}$ and binary cross-entropy loss $L_{ST}$. Specifically,

$$L_{PH} = - \frac{1}{m} \sum_{t=1}^{m} \alpha p_t \log \hat{p}_t$$

$$L_{ST} = - \frac{1}{m} \sum_{t=1}^{m} \left[ \alpha e_t \log \hat{e}_t + (1 - e_t) \log (1 - \hat{e}_t) \right]$$

where $\alpha$ is a balance factor, $m$ is the length of the reference phoneme sequence, $\hat{p}$ and $p$ refer to the predicted phonemes and the reference phonemes, $\hat{e}$ refers to the predicted error states, $e$ refers to the true error states by comparing the predicted and the reference phonemes. These losses are combined as,

$$\mathcal{L} = \mathcal{L}_{CTC} + \beta \mathcal{L}_{ST} + \gamma L_{PH}$$

for the objective of model training. In our experiments, we set $\alpha = 5$, $\beta = 1$, and $\gamma = 0.5$.

We further employ an ensemble scheme to combine the predictions for final MDD decision. The ensemble is based on the following rule. For each item in reference phonemes, if the corresponding error state is recognized as positive (i.e., error probability is larger than 0.5), but the recognized phoneme from the CTC decoder is the same as the reference phoneme, we consider that the recognized result is not reliable. The results of CCA-MDD is marked by error mark serr. Otherwise, the recognized phoneme would be taken as the final results. An example is given in Table 1. CCA-MDD (CTC) and CCA-MDD (ST) present the outputs from the CTC decoder and the error state classifier respectively. In contrast to ‘pronounced phonemes’ according to a dictionary, ‘pronounced phonemes’ denotes the phones that the user has actually pronounced. In this example, the word ‘she’ is not present in the reference text but is pronounced in the speech. Our CTC decoder still recognizes the word successfully. The CTC decoder fails to recognize the phoneme ‘T’ in the last column. The corresponding probability of error state is also below 0.5. A missing error (marked as ‘-’) is therefore issued in the final CCA-MDD result. The CCA-MDD output are compared against the pronounced phonemes as in ‘Detection Type’.

### 3. EXPERIMENTAL EVALUATION

#### 3.1. Experimental Setup

**Datasets** We conduct our experiments on two publicly available English corpora, TIMIT [20] and L2-ARCTIC corpus [21]. TIMIT contains recordings of 630 speakers of 8 US English dialects. Each speaker reads out 10 sentences. All the recordings are well labeled with 61-phone transcriptions. L2-ARCTIC is a non-native English corpus. We perform our experiments with version 5 of L2-ARCTIC. The corpus consists of recordings from 24 speakers (12 males and 12 females) of six different first languages (Hindi, Korean, Mandarin, Spanish, Arabic and Vietnamese). Phone-level transcriptions are available with a 48-phone set, plus an additional symbol /err/ for unclear pronunciation. We first convert the transcriptions of the two corpora into TIMIT 39-phone set according to the CMU Pronouncing Dictionary (CMUDict) [22] for convenience of cross-corpus usage. We take the recordings of six speakers (NJS, TLV, TNI, TXHC, YKMK, ZHAA) from L2-ARCTIC as the test set. We take the remaining 18 speakers of L2-ARCTIC and TIMIT as training set. There are 7.2h speech data for training and 0.88h data for testing.

**Model training** When speakers pronounce the utterances correctly, reference phonemes and pronounced phonemes are the same. The model is prone to over-fitting during training. We avoid over-fitting by augmenting reference phoneme labels. We randomly insert additional phonemes, delete or substitute the original phonemes of the reference phonemes to simulate mispronunciation. We train the model in two stages as shown in Fig. 3. Namely, first, we pre-train the IAE and the CTC decoder as an ASR model with the original reference phoneme labels in the training set (with 1000 steps). Then, we take the weights of the pre-trained components to initialize the corresponding modules of CCA-MDD. We fine-tune the whole model with the augmented training set.

**Model configuration** We refer readers to [18] for the details of the conv-Transformer blocks and acoustic feature extraction in the IAE.
Table 2. Comprehensive performance comparison. In ‘Canonicals’, true acceptance (TA) indicates correct predictions, while false rejection (FR) denotes the failure to accept correct pronunciation. In ‘Mispronunciation’, false acceptance (FA) indicates the models do not detect mispronounced phones, while true rejection (TR) indicates that the models detect the mispronounced phones. TR is further analysed with correct diagnosis and diagnosis errors. The F-Measure (F1) is calculated as $2 \times \text{precision} \times \text{recall} / (\text{precision} + \text{recall})$, where $\text{precision} = \frac{\text{TA}}{\text{TA} + \text{FA}}$ and $\text{recall} = \frac{\text{TR}}{\text{TR} + \text{FR}}$ respectively.

| Models          | True Acceptance | False Rejection | False Acceptance | True Rejection | Mispronunciation | F1(%) | PER(%) |
|-----------------|-----------------|-----------------|------------------|---------------|------------------|-------|--------|
| SED-MDD [10]    | 91.99% (25576)  | 8.01% (2226)    | $\text{TA} = \frac{S + D + I}{N}$, where $N$ is total number of labelled phones, and $S$, $D$ and $I$ represent the counts of the substitution, deletion and insertion errors respectively. The PER results are shown in the last column of Table 2. CCA-MDD (CTC) corresponds to the output from the CTC decoder. CCA-MDD is the final model output with ensemble. CCA-MDD (CTC) achieves a low PER of 11.84%. The results support the effectiveness of the integrated text-acoustic modeling and CCA, and promise the potential for MDD problem.

For the rest of CCA-MDD, all multi-head attentions in Transformer layers and CCA share the same setting. There are 6 heads for each layer. For the rest of CCA-MDD, all multi-head attentions in Transformer layers and CCA share the same setting. There are 6 heads for each layer.

3.2. Performance on Phone Recognition

The performance of phone recognition is a key factor for MDD. We first evaluate phone recognition accuracy with phoneme error rate (PER) as the metric, where

$$\text{PER} = \frac{S + D + I}{N},$$

where $N$ is total number of labelled phones, and $S$, $D$ and $I$ represent the counts of the substitution, deletion and insertion errors respectively. The PER results are shown in the last column of Table 2. CCA-MDD (CTC) corresponds to the output from the CTC decoder. CCA-MDD is the final model output with ensemble. CCA-MDD (CTC) achieves a low PER of 11.84%. The results support the effectiveness of the integrated text-acoustic modeling and CCA, and promise the potential for MDD problem.

3.3. Performance on MDD

We next perform evaluation to MDD tasks. We report the results with the metrics following [11] [7]. The results are reported in Table 2. Our proposed CCA-MDD models achieve competitive scores under most of the metrics. Especially, CCA-MDD (CTC) achieves true acceptance and false rejection of 95.34% and 4.66% respectively. The results indicate that our model can well recognize correct pronunciations. For mispronunciation, our model also achieves reasonable diagnosis accuracy of 80.95% for true rejection. However, the trade-off of CCA-MDD (CTC) is increased false acceptance rate. We suspect that under streaming configuration, the decoder learns to produce recognition output close to the reference phonemes due to biased linguistic cues. The high false accepted rate is alleviated by our ensemble mechanism. CCA-MDD reduces false acceptance rate from 48.90% to 32.51%, and achieves F1 score of 60.78%. For L2-ARCTIC test set, SED-MDD [10] achieves high F1 score of 62.56%. The high F1 score is probably contributed by force alignment of phoneme transcriptions with speech data with an external force-alignment tool. Note that our CCA-MDD model is an e2e model which does not apply force alignment during training and inferring. Note that the ensemble mechanism does not update phone recognition results, we do not re-calculate PER. The ensemble mechanism sometimes outputs binary state set to CCA-MDD as shown in Table 2 diagnosis accuracy is not applicable.

Table 3. Result comparison on the Recall, Precision and F1 metrics.

| Models          | Recall(%) | Precision(%) | F1(%) |
|-----------------|-----------|--------------|-------|
| SED-MDD [10]    | 36.99     | 69.36        | 62.56 |
| w2v2.0-XLSR+TIMIT [14] | 62.86     | 58.20        | 60.44 |
| GOP [24]        | 35.42     | 52.88        | 42.42 |
| CTC-ATT [23]    | 46.57     | 70.28        | 56.02 |
| CNN-RNN-CTC+VC [13] | 56.04     | 56.12        | 56.08 |
| CCA-MDD (CTC)   | 51.01     | 64.65        | 57.03 |
| CCA-MDD         | 67.49     | 55.29        | 60.78 |

We compare our model with five other MDD approaches in terms of recall and precision. The results are shown in Table 3. CCA-MDD achieves high recall and F1. Although the frame-wise CCA-MDD (CTC) operates at streaming mode, the performance is still comparable to other approaches. We notice that the high precision of CTC-ATT [23]. CTC-ATT utilizes a hybrid of CTC and attention mechanism on whole input speech utterance. The model pays more attention to capture context of acoustic features in addition to linguistic features which achieves lower false acceptance rate. On the other hand, due to streaming property of CCA-MDD (CTC), the CTC decoder only relies on a small part of future input with a look-ahead window of 60ms, leading to slightly inferior precision. We consider this as a trade-off for low latency.

4. CONCLUSION

To our best knowledge, our work is the first attempt to apply an end-to-end neural model for streaming mispronunciation detection and diagnosis problem. We propose a framework named CCA-MDD, which employs conv-Transformer networks for streaming acoustic features, a coupled cross-attention (CCA) to fully integrate the linguistic and acoustic cues, and a multi-task trained ensemble decoder as the final classifier. Experiments on public benchmarks demonstrate that CCA-MDD achieves comparable performance to offline models, even executing in streaming mode. As a future work, we would extend this framework to embrace more related functions such as word or sentence-level GOP, and accent identification. We would further improve CCA to allow the bottom attention to be conditioned on partial-context, making the ensemble model also run on streaming mode.
5. REFERENCES

[1] Pamela M Rogerson-Revell, “Computer-assisted pronunciation training (CAPT): Current issues and future directions,” *RELC Journal*, vol. 52, no. 1, pp. 189–205, 2021.

[2] Silke M Witt and Steve J Young, “Phone-level pronunciation scoring and assessment for interactive language learning,” *Speech communication*, vol. 30, no. 2-3, pp. 95–108, 2000.

[3] Hao Huang, Hailu Xu, Ying Hu, and Gang Zhou, “A transfer learning approach to goodness of pronunciation based automatic mispronunciation detection,” *The Journal of the Acoustical Society of America*, vol. 142, no. 5, pp. 3165–3177, 2017.

[4] Wenwei Dong and Yanlu Xie, “Normalization of GOP for Chinese mispronunciation detection,” 2019 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), pp. 1004–1008, 2019.

[5] Wernping Hu, Yao Qian, F. Soong, and Yong Wang, “Improved mispronunciation detection with deep neural network trained acoustic models and transfer learning based logistic regression classifiers,” *Speech Communication*, vol. 67, pp. 154–166, 2015.

[6] M. Maqsood, H. A. Habib, S. Anwar, Mustansar Ali Ghazanfar, and Tabassam Nawaz, “A comparative study of classifier based mispronunciation detection system for confusing,” *Nucleus*, vol. 54, pp. 114–120, 2017.

[7] Zhan Zhang, Yuehai Wang, and Jianyi Yang, “Text-conditioned transformer for automatic pronunciation error detection,” *Speech Communication*, vol. 130, pp. 55–63, 2021.

[8] Binghui Lin and Liyuan Wang, “Attention-based multi-encoder automatic pronunciation assessment,” in *2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2021, pp. 7743–7747.

[9] Minglin Wu, Kun Li, Wai-Kim Leung, and Helen Meng, “Transformer based end-to-end mispronunciation detection and diagnosis,” *Proc. Interspeech 2021*, pp. 3954–3958, 2021.

[10] Yiqing Feng, Guanyu Fu, Qingcai Chen, and Kai Chen, “SED-MDD: Towards sentence dependent end-to-end mispronunciation detection and diagnosis,” in *2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020, pp. 3492–3496.

[11] Wai-Kim Leung, Xunying Liu, and Helen Meng, “CNN-RNN-CTC based end-to-end mispronunciation detection and diagnosis,” in *2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2019, pp. 8132–8136.

[12] Alex Graves, Santiago Fernández, Faustino Gomez, and Jürgen Schmidhuber, “Connectionist temporal classification: Labelling unsegmented sequence data with recurrent neural networks,” in *Proceedings of the 23rd International Conference on Machine Learning*, 2006, p. 369–376.

[13] Kaiqi Fu, Jones Lin, Dengfeng Ke, Yanlu Xie, Jinsong Zhang, and Binghuai Lin, “A full text-dependent end to end mispronunciation detection and diagnosis with easy data augmentation techniques,” 2021, arXiv:2104.08428.

[14] Linkai Peng, Kaiqi Fu, Binghuai Lin, Dengfeng Ke, and Jinsong Zhan, “A study on fine-tuning wav2vec2.0 model for the task of mispronunciation detection and diagnosis,” *Proc. Interspeech 2021*, pp. 4448–4452, 2021.

[15] Longfei Yang, Kaiqi Fu, Jinsong Zhang, and Takahiro Shinozaki, “Pronunciation erroneous tendency detection with language adversarial represent learning,” in *Proc. Interspeech 2020* 2020, pp. 3042–3046.

[16] W. Menzel, Daniel Herron, Rachel Morton, D. Pezzotta, P. Bonaventura, and Peter Howarth, “Interactive pronunciation training,” *ReCALL*, vol. 13, pp. 67 – 78, 2001.

[17] Yanzhang He, T. Sainath, Rohit Prabhavalkar, Ian McGraw, R. Alvarez, Ding Zhao, David Rybach, Anjuli Kannan, Y. Wu, Ruoming Pang, Qiao Liang, Deepthi Bhatia, Yuan Shangguan, Bo Li, G. Pandak, K. Sim, Tom Bagby, Shuo-Yin Chang, Kanishka Rao, and Alexander Gruenstein, “Streaming end-to-end speech recognition for mobile devices,” *2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 6381–6385, 2019.

[18] Wenyong Huang, Wenchao Hu, Yu Ting Yeung, and Xiao Chen, “Conv-Transformer Transducer: Low latency, low frame rate, streamable end-to-end speech recognition,” in *Proc. Interspeech 2020*, 2020, pp. 5001–5005.

[19] Bo Li, Shuo-Yin Chang, T. Sainath, Ruoming Pang, Yanzhang He, Trevor Strohman, and Yonghui Wu, “Towards fast and accurate streaming end-to-end asr,” *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 6069–6073, 2020.

[20] John S Garofolo, Lori F Lamel, William M Fisher, Jonathan G Fiscus, and David S Pallett, “DARPA TIMIT acoustic-phonetic continuous speech corpus CD-ROM,” *NASA STI/Recon technical report N*, vol. 93, pp. 27403, 1993.

[21] Guanlong Zhao, Sinem Sonsaat, Alif Silpachai, Ivana Lucic, Evgeny Chukharev-Hudilainen, John Levis, and Ricardo Gutierrez-Osuna, “L2-ARCTIC: A non-native English speech corpus,” in *Proc. Interspeech 2018*, 2018, pp. 2783–2787.

[22] “The CMU pronouncing dictionary,” [https://github.com/cmusphinx/cmudict](https://github.com/cmusphinx/cmudict) [Online; accessed 6-October-2021].

[23] Bi-Cheng Yan, Meng-Che Wu, Hsiao-Tsung Hung, and Berlin Chen, “An end-to-end mispronunciation detection system for L2 English speech leveraging novel anti-phone modeling,” in *Proc. Interspeech 2020*, 2020, pp. 3032–3036.

[24] Bi-Cheng Yan and Berlin Chen, “End-to-end mispronunciation detection and diagnosis from raw waveforms,” 2021, ArXiv:abs/2103.03023.