HIERARCHICAL PRONUNCIATION ASSESSMENT WITH MULTI-ASPECT ATTENTION

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ABSTRACT
Automatic pronunciation assessment is a major component of a computer-assisted pronunciation training system. To provide in-depth feedback, scoring pronunciation at various levels of granularity such as phoneme, word, and utterance, with diverse aspects such as accuracy, fluency, and completeness, is essential. However, existing multi-aspect multi-granularity methods simultaneously predict all aspects at all granularity levels; therefore, they have difficulty in capturing the linguistic hierarchy of phoneme, word, and utterance. This limitation further leads to neglecting intimate cross-aspect relations at the same linguistic unit. In this paper, we propose a Hierarchical Pronunciation Assessment with Multi-aspect Attention (HiPAMA) model, which hierarchically represents the granularity levels to directly capture their linguistic structures and introduces multi-aspect attention that reflects associations across aspects at the same level to create more connotative representations. By obtaining relational information from both the granularity- and aspect-side, HiPAMA can take full advantage of multi-task learning. Remarkable improvements in the experimental results on the speechocean762 datasets demonstrate the robustness of HiPAMA, particularly in the difficult-to-assess aspects.

Index Terms— Pronunciation assessment

1. INTRODUCTION

Computer Assisted Pronunciation Training (CAPT) systems provide extensive feedback to non-native (L2) language learners about their pronunciation along with automatically assessed scores [1, 2]. Their fairness and objectivity have led to extensive studies on the automatic pronunciation assessment task, which is an indispensable component of CAPT.

Although most early pronunciation assessment systems only evaluated a single phoneme-level score [3, 4, 5], current studies have evaluated other aspects of word or utterance such as prosody, and especially stress, fluency, and intonation, but using separate models [6, 7, 8]. Recently, there has been an attempt to score multiple aspects at more than one granularity level of pronunciation using a single model, named GOPT [9], emphasizing that different aspects of multi-granularity are indeed correlated and that jointly learning them leads to comprehensive representation. Their structure, which predicts all aspects at all granularity levels in parallel, has significantly contributed to the pronunciation assessment tasks.

However, phonemes, words, and utterances have strong linguistic dependencies [2], which may not be captured by a parallel structure. This also leads to a lack of consideration of the internal interactions across different aspects evaluated at the same granularity. Moreover, although GOPT outperforms previous systems in most aspects, the assessment of the utterance Completeness is extremely inferior compared to other aspects. An accurate evaluation is equally required for all aspects, thus improving the scoring quality of poor-performance aspects is a persistent challenge in multi-task learning.

In this paper, we propose a novel model named Hierarchical Pronunciation Assessment with Multi-aspect Attention (HiPAMA) that assesses the phoneme-, word-, and utterance-level scores one level at a time, incrementally encoding the pronunciation. HiPAMA directly incorporates the syntactic structure of an utterance, which is made of words that comprise phonemes. Furthermore, we introduce a multi-aspect attention mechanism, which attends to other aspects at the same level to obtain more representative features considering that aspects are correlated in nature. Unlike the Transformer encoder that fully connects all nodes, our model modulates each aspect-assessment task within each level.

We conduct experiments on the publicly available speechocean762 dataset [10], which includes one phoneme-, three word-, and five utterance-level score labels. HiPAMA remarkably outperforms the robust baseline [9] on all three granularity levels of assessment tasks, achieving state-of-the-art results on most of the aspects. In particular, the assessment for utterance Completeness has been significantly enhanced. The results show that HiPAMA is a robust architecture for multi-output regression with an explicit output hierarchy.

2. RELATED WORK

Early works on automatic pronunciation assessment assessed a single aspect score only at the phoneme level [3, 4, 5] or various aspect scores of word or utterance levels separately [6, 7, 8]. Emphasizing that phonemes, words, and sentences are not independent of each other, a hierarchical network that outputs a single score at each granularity has been proposed...
HiPAMA mainly includes three components at different granularity levels: phoneme, word, and utterance level. At each level, HiPAMA contains modulized layers for each aspect-assessment task (Figure 1).

3. MODEL DESCRIPTION

3.1. Model Inputs

For the input parts of the model, we follow the baseline model [9] for a fair comparison. In particular, the automatic speech recognition (ASR) acoustic module takes the audio and its transcription as the input and predicts the sequence of frame-level phonetic posterior probabilities. These probabilities are transformed into 84-dimensional GOP features: level phonetic posterior probabilities. These probabilities are transformed into 84-dimensional GOP features:

$$LPP(p_1), \ldots, LPP(p_{12}), LPR(p_1|p), \ldots, LPR(p_{12}|p)$$  

(1)

where $LPP$ and $LPR$ denote the log phone posterior and log posterior ratio of a phone $p$, respectively. A phone $p$ is one of the pure phones in the acoustic model. Then, a dense layer projects the GOP features into 24 dimensions [9]. Apart from GOP features, phoneme embedding is computed by projecting each phoneme-level one-hot encoding into 24 dimensions. Then, the GOP features and phoneme embedding are added and used as the input to our model.

3.2. Model Architecture

Unlike the previous method that processes all granularity levels in parallel, the proposed method hierarchically represents each level of pronunciation. At each level, after obtaining the final representations for different aspects, a regression head for each aspect is followed to obtain the final aspect score.

First, for the phoneme-level representation, the long short-term memory (LSTM) [13] is applied to directly capture the sequential information of phonemes within the utterance [14]. Then, a multi-head self-attention layer from [11] is used to obtain the comprehensive contextual information for accurate assessment, which is then followed by a convolutional layer. The reason for utilizing a convolutional layer for phoneme-level representation is to better capture the local information corresponding to phonemes [15, 16].

For word-level aspect scoring, encapsulated phoneme-level representations are passed to a separate module that assesses a different aspect. In the process of each module obtaining a representation for a specific aspect, our multi-aspect attention mechanism that computes attention scores with non-target aspect representations is introduced. This is motivated by the trait-attention mechanism applied to the automated essay scoring task [17], where each trait refers to the relevant information of other traits, and the term trait is similar to the term aspect in this task. We hypothesize that our multi-aspect attention method helps to better assess tricky aspects by accessing information about easy-to-assess aspects. In particular, first, for the $n$-th target aspect representation $a^n$, non-target aspect representations $[a^1, \ldots, a^{n-1}, a^{n+1}, \ldots, a^N]$ are concatenated into $S^m$. Then, a non-target matrix $A'$ is obtained by applying attention pooling [18] to $S^m$. For the cross-attention between the target aspect representation and non-target aspects, the following operation is performed:

$$v_i^n = \frac{\exp(score(a^n, A_{i}'))}{\sum_k \exp(score(a^n, A_k'))}$$  

(2)

$$m^n = \sum_i v_i^n A_i'$$  

(3)

$$r^n = a^n + m^n$$  

(4)

where the multi-aspect attention vector $m^n$ is defined with the attention weight $v_i^n$. Then, by summing up the target as-
Table 1. Experimental results with average MSE (phoneme level) and PCC (phoneme, word, and utterance level) scores and standard deviations of five different runs; Acc is Accuracy; Comp is Completeness; -implement is implemented baseline model.

| Model                          | Phoneme Score | Word Score (PCC) | Utterance Score (PCC) |
|-------------------------------|---------------|------------------|-----------------------|
|                               | Acc(MSE ↓)    | Acc(PCC ↑)       | Acc ↓ | Stress ↓ | Total ↑ | Acc ↑ | Comp ↑ | Fluency ↑ | Prosody ↑ | Total ↑ |
| LSTM                          | 0.089         | 0.587            | 0.311 | 0.297    | 0.524    | 0.077 | 0.123 | 0.741     | 0.744      | 0.743    |
|                               | ±0.002        | ±0.014           | ±0.014 | ±0.012  | ±0.011    | ±0.004 | ±0.143 | ±0.010    | ±0.006      | ±0.006    |
| Gong et al.[9]                | 0.085         | 0.612            | 0.333 | 0.291    | 0.549    | 0.074 | 0.135 | 0.753     | 0.760      | 0.742    |
|                               | ±0.001        | ±0.003           | ±0.004 | ±0.030  | ±0.006    | ±0.004 | ±0.039 | ±0.008    | ±0.006      | ±0.005    |
| Gong et al.[9]-implement      | 0.086         | 0.609            | 0.330 | 0.299    | 0.548    | 0.072 | 0.119 | 0.762     | 0.760      | 0.738    |
|                               | ±0.001        | ±0.004           | ±0.003 | ±0.018  | ±0.008    | ±0.003 | ±0.264 | ±0.003    | ±0.008      | ±0.004    |
| HiPAMA                        | 0.084         | 0.616            | 0.575 | 0.320    | 0.591    | 0.730 | 0.276 | 0.749     | 0.751      | 0.754    |
|                               | ±0.001        | ±0.004           | ±0.004 | ±0.021  | ±0.004    | ±0.002 | ±0.177 | ±0.001    | ±0.002      | ±0.002    |

3.3. Loss Function

We use mean squared error (MSE) loss, which is commonly used for the pronunciation assessment task, as the loss function. The total loss is calculated as the sum of each granularity-level loss, each of which is an averaged loss of multiple aspects at that level:

\[
L_{\text{total}} = \sum_{m=1}^{M} \frac{1}{N} \sum_{n=1}^{N} L_{mn}
\]  

where \(M\) and \(N\) are the total numbers of granularity levels and aspects, respectively. \(M\) is 3 when handling three levels.

4. EXPERIMENTS

For the experiments, we use the publicly available speech-aachen762 dataset [10], which is well designed for the multi-aspect multi-granularity pronunciation assessment task. It has score labels for three assessment granularity levels: utterance-, word-, and phoneme-level. For each level, there are multiple aspect scores: 1) Accuracy, Completeness, Fluency, Prosody, and Total score for utterance-level; 2) Accuracy, Stress, and Total score for word-level; and 3) Accuracy score for phoneme-level. As in the baseline system [9], the utterance and word scores are scaled from (0-10) to (0-2) to achieve the same scale as the phoneme scores, and the same training and test set as the baseline system are used, each of which comprises 2500 utterances.

For a fair comparison, configurations other than the proposed parts are set to the same as the baseline, including the ASR acoustic model trained with Librispeech [19] 960-hour data. Specifically, HiPAMA is trained with the Adam optimizer, with a training epoch of 100, an initial learning rate of 1e-3, batch size of 25. Four heads are set for multi-head attention, and the dropout rate is set to 0.2 for utterance-level multi-head attention. Five runs with different random seeds are performed for all models, whose mean and standard deviation are reported. We use the Pearson correlation coefficient (PCC) as the evaluation metric along with MSE for the phoneme score as in [9].

5. RESULTS AND DISCUSSION

We compare HiPAMA with the previous state-of-the-art baseline model [9], which uses a 3-layer Transformer encoder, and the LSTM-based model, which was mainly compared with the baseline model (Table 1). The results clearly demonstrate the strength of HiPAMA, which exhibit the highest PCC scores for most of the assessment tasks.

Assessment performance is remarkably improved for all aspects at all levels (average absolute improvement of 4.9%), except Fluency and Prosody utterance scores (1.3% and 0.9% absolute decrease). These two aspects already had higher PCC values than other aspects, and HiPAMA shows comparable values with only a slight decrease. In particular, significant improvements are observed in the utterance Completeness assessment task (131.9% relative and 15.7% absolute improvements), where previous models perform poorly.

Further examination of multi-aspect attention weights enhances the explainability of our method, revealing other aspects that are being referenced when scoring a specific aspect (Figure 2). For example, at the word level (a), the Accuracy aspect highly focuses on the Stress representation, while the utterance-level (b) Accuracy aspect gives high weights to Prosody. This result indicates that our method reflects the real-world assessment process because the scoring metric of word-level Accuracy includes the criterion of accents [10], and the accuracy of sentence-level pronunciation closely depends on the prosody [20] in actual language learning. For the scoring of weak aspects, such as word Stress and utterance Completeness, the weight distribution is very consistent,
Table 2. Ablation results with average MSE (for phoneme level) and PCC (for phoneme, word, and utterance level) scores of five different runs. Hi and MA denote hierarchical structure and multi-aspect attention mechanism, respectively.

| Model               | Phoneme Score | Word Score (PCC) | Utterance Score (PCC) |
|---------------------|--------------|------------------|-----------------------|
|                     | Phoneme ↑    | PCC ↑            | Total ↑               |
|                     | Word ↑       | Stress ↓         | Fluency ↑             |
|                     | Stress ↑     | Total ↑          | Prosody ↑             |
|                     | PCC ↑        | Total ↑          | Total ↑               |
| w/o Hi w/o MA       | 0.085        | 0.609            | 0.566 0.299 0.582    |
| w/o Hi w/ MA        | 0.085        | 0.614            | 0.571 0.323 0.586    |
| w/ Hi w/ MA (HiPAMA)| 0.084        | 0.616            | 0.575 0.320 0.591    |

Fig. 2. Multi-aspect attention weights (run with seed 0) for other aspects when predicting each aspect score.

Table 3. Effect of the number of parameters (# param). Because of the space limit, only the average score of the aspects has been reported for each granularity.

| Model       | # param | Phoneme    | Word     | Utterance |
|-------------|---------|------------|----------|-----------|
| 3layer-base | 26.58k  | 0.086 0.609| 0.459    | 0.618     |
| 4layer      | 33.73k  | 0.086 0.609| 0.452    | 0.628     |
| HiPAMA      | 31.64k  | 0.084 0.616| 0.495    | 0.652     |

5.1. Ablation Studies

To investigate the effect of each component of HiPAMA, we conduct ablation studies in Table 2. First, we experiment with a model without hierarchical structure and multi-aspect attention, which predicts all aspects of all granularity levels in parallel right after the LSTM, multi-head self-attention, and convolutional layer (1st row). Second, we evaluate a model in which only multi-aspect attention is added to the first model (2nd row). Note that HiPAMA is a model with a hierarchical structure applied to the second model.

Because of the addition of multi-aspect attention, the performance improvements for previously difficult-to-assess aspects (word Stress and utterance Completeness) are considerably greater than other aspects. Furthermore, applying the hierarchical structure affords overall performance improvements; particularly in the last step, utterance level, the assessment performance significantly increased. The remarkable point is that jointly applying both of our approaches increases their synergistic impact for multiple aspect-assessment tasks.

5.2. Effects of Model Size

The baseline model uses a 3-layer Transformer encoder of 26.58k parameters, while HiPAMA has 31.64k parameters. To prevent a favorable condition for HiPAMA regarding the model size, we additionally compare HiPAMA with a larger baseline model: a 4-layer Transformer encoder-based model of 33.73k parameters (Table 3). Although the baseline model itself slightly improves as the number of parameters increases, HiPAMA still outperforms both models even with a slightly smaller model size. These results prove that the robustness of HiPAMA is not due to the increased number of parameters.

6. CONCLUSION

In this study, we propose the HiPAMA model. Our hierarchical structure is designed to capture the linguistic structures of phonemes, words, and utterances, while our multi-aspect attention mechanism enables representative encoding of internal connections between aspects at a specific level. Experimental results on the speechocean762 dataset verify that the HiPAMA architecture is indeed effective by outperforming the previous state-of-the-art model.

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