ABSTRACT
End-to-end automatic speech recognition (ASR) has achieved promising results. However, most existing end-to-end ASR methods neglect the use of specific language characteristics. For Mandarin Chinese ASR tasks, pinyin and character as writing and spelling systems respectively are mutual promotion in the Mandarin Chinese language. Based on the above intuition, we investigate types of related models that are suitable but not for joint pinyin-character ASR and propose a novel Mandarin Chinese ASR model with dual-decoder Transformer according to the characteristics of the pinyin transcripts and character transcripts. Specifically, the joint pinyin-character layer-wise linear interactive (LWLI) module and phonetic posteriorgrams adapter (PPGA) are proposed to achieve inter-layer multi-level interaction by adaptively fusing pinyin and character information. Furthermore, a two-stage training strategy is proposed to make training more stable and faster convergence. The results on the test sets of AISHELL-1 dataset show that the proposed Speech-Pinyin-Character-Interaction (SPCI) model without a language model achieves 9.85% character error rate (CER) on the test set, which is 17.71% relative reduction compared to baseline models based on Transformer.

Index Terms—Mandarin Chinese ASR, dual-decoder, Transformer, interaction, pinyin and character
In this paper, we want the model to leverage the pinyin information readily available while still emitting characters as final output and displaying pinyin transcripts to users alongside the character transcripts is more friendly to users. The total number of pinyin syllables is thousands while the number of Chinese characters is tens of thousand, which reduces the difficulty of syllable choices in the decoder. Regardless of tone, there are a total of 413 pinyin syllables.

3. DUAL-DECODER TRANSFORMER E2E ASR

3.1. Speech-Transformer

Speech-Transformer [8, 9, 10] is an end-to-end model for ASR based on Transformer which transforms the speech features directly to the corresponding character sequences. The Transformer based model has become the basic architecture of sequence-to-sequence attention-based model [13] and achieves state-of-the-art performance in various ASR tasks. In this paper, all the models are based on Speech-Transformer.

3.2. Related Model Architectures

Figure 1 is the diagram of related end-to-end models which are proposed in applications such as speech translation [16, 17], etc., rather than joint pinyin-character ASR tasks. The specific model architecture of each type is shown in Table 1. They are as follows:

**Single.** We train two Speech-Transformer models separately, one of which only emits pinyin transcripts as output (PinyinOnly), and the other only emits character transcripts as output (CharacterOnly).

**Two-stage.** The model (Pinyin-Character-Direct) consists of one encoder and two decoders, where the two decoders are directly connected.

**Triangle.** On the basis of the Two-stage model category, we pass the encoded speech to the character decoder by adding encoder-decoder attention to the character decoder layer (Pinyin-Character-Triangle).

**Multi-task.** We train two models. One is Speech-Transformer model only emitting character transcripts as output which is initialized with the pre-trained PinyinOnly model (Pinyin-Character-Sequence). The other model consists of one encoder and two decoders, where the two decoders are parallel without interaction (Pinyin-Character-Parallel).

**Interactive.** We train two models consisting of two layer-wise interactive decoders with attention, one of which is the pinyin-to-character unilateral model (UnilateralInteractiveAttention), the other is the bilateral model (BilateralInteractiveAttention) [16].

3.3. Layer-wise Linear Interactive Module

Since the length of character transcript and pinyin transcript for the same speech input is the same and tokens at the same position of the two transcripts correspond to the same speech segment, there is a linear correlation in the output distribution of the attention components of the decoder, but the distribution space mismatch.

We propose the layer-wise linear interactive (LWLI) module to integrate the representations of pinyin ASR and character ASR tasks which is shown in Figure 2. It can be defined as:

\[
out_{\text{char}} = Mapping(input_{\text{pinyin}}) + input_{\text{char}} \\
out_{\text{pinyin}} = Mapping(input_{\text{char}}) + input_{\text{pinyin}}
\]

where \(input_{\text{pinyin}}\) and \(input_{\text{char}}\) are the representation input of pinyin and character, respectively. \(out_{\text{pinyin}}\) and \(out_{\text{char}}\)
are generated output of pinyin and character, respectively. $Mapping()$ is an MLP.

### 3.4. Phonetic Posteriorgrams Adapter

Phonetic Posteriorgram (PPG) is a graph in which the x-axis is time and the y-axis contains distinct phonetic classes representing the posterior probabilities of each phonetic class for each specific time frame of one transcript $[18]$. Similar to the LWLI module, pinyin PPG and character PPG are also strongly related. Different from bilateral design in the layer-wise linear interactive module, PGA only uses unilateral, which can be defined as:

$$PPG_{char} = Mapping(PPG_{pinyin}) + PPG_{char} \quad (3)$$

where $PPG_{pinyin}$ and $PPG_{char}$ are the pinyin PPG and character PPG, respectively. $Mapping()$ is an MLP, here we use one fully connected layer.

### 3.5. Two-stage Training Strategy

We train the dual-decoder model from a fix initialization to minimize the combined loss:

$$L_{combine}(\theta_e, \theta_1, \theta_2) = \lambda L_{pinyin}(\theta_e, \theta_1) + (1 - \lambda) L_{char}(\theta_e, \theta_2) \quad (4)$$

where $L_{pinyin}$, $L_{char}$ donate the cross-entropy loss of the pinyin decoder and character decoder, respectively. $\theta_e$, $\theta_1$, $\theta_2$, represent the parameters of the shared encoder, pinyin decoder and character decoder, respectively. $\lambda$ is a hyperparameter. Here we adopt a two-stage training method:

**Stage 1.**

(1) Train two single models for pinyin transcript and character transcript separately.

(2) Initialize the proposed model.

2.1) Initialize the encoder and pinyin decoder of the proposed model with the pre-trained weights of the single pinyin model.

2.2) Initialize the character decoder with the pre-trained weights of the single character model.

2.3) Randomly initialize the interaction module between the pinyin decoder and the character decoder.

**Stage 2.**

Train the whole model at the same time with the combined loss.

### 4. EXPERIMENTAL DETAILS

#### 4.1. Data and Evaluation Metrics

In this paper, we use the AISHELL-1 dataset in 16 kHz WAV format to verify the performance of all the models. All speech is represented as an 80-dimensional filterbank with a frame length of 25ms and a frame shift of 10ms, extended with temporal first and second-order differences. All feature sequences are normalized using the mean and variance of each audio sample.

We extract the pinyin transcriptions using a free python tool $[11]$. In this paper, pinyin syllables consist of 413 syllables without tone which the character set consists of 4333 characters without $<sos> <$cos> <$pad> tags.

In addition to using character error rate (CER), we also design an evaluation metric to compare the alignment degree (AD) of generated pinyin transcript and character transcript for dual-decoder models which is defined as follows:

$$AD(y_{char}, y_{pinyin}) = \frac{\sum_i Same(y_{convert}, y_{i, char})}{\text{len}(y_{convert})} \quad (5)$$

$$y_{convert}^{pinyin} = F_{char->pinyin}(y_{char}) \quad (6)$$

$$Same(a, b) = \begin{cases} 1 & a = b \\ 0 & a \neq b \end{cases} \quad (7)$$

where $F_{char->pinyin}$ converts generated character sequence to pinyin sequence by mentioned automatic python tool. The higher AD, the higher the correlation between the generated pinyin sequence and character sequence.

### 4.2. Model Details and Inference

The proposed model includes 6 encoder layers, 6 pinyin decoder layers and 6 character decoder layers. The Transformer consists of dimensional $dim_{inner} = 2048$, $dim_{model} = 512$, $dim_{emb} = 512$, $dim_{key} = 64$ and $dim_{value} = 64$. Use the same optimizer settings as $[19]$. To further avoid overfitting, dropout is used with probability 0.1. All models are trained for 150 epochs using a batch size 16 and stopped early. At test time, we use beam search with a 5 beam width to output the best-decoded sentence for all the experiments and restrict the generated pinyin transcript and character transcript with the same length. Our code is an improvements version based on source code $[1]$.

### 5. EXPERIMENTAL RESULTS

#### 5.1. Compare proposed model to related models

Table $[1]$ shows the CER and alignment degree scores of the related models and our proposed method on AISHELL-1 dataset. All the dual-decoder models are initialized with pre-trained single models. Firstly, we can observe that the proposed SPCI model achieves the best performance compared to all the other models. Secondly, we find all the dual-decoder models achieve competitive results, consistently

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1. https://github.com/mozillazg/python-pinyin
2. https://github.com/foamliu/Speech-Transformer
surpass single decoder models of PinyinOnly and CharacterOnly. Thirdly, the Pinyin-Character-Sequence model achieves better results compared to the CharacterOnly model, which shows pinyin ASR is an effective pre-training task to improve character ASR task. Finally, the PinyinOnly model achieves considerably lower CER scores compared to the CharacterOnly model, which is consistent with the analysis of pinyin and character for Mandarin Chinese ASR in Section 2.

### 5.2. Effect of main components and training strategy

To explore how main components and training strategy contribute to performance, we conduct an ablation experiment. As is shown in Table 2, we can find that the layer-wise linear interactive module and the PPGA module effectively reduce CER scores on AISHELL-1 dataset.

| Method              | Pinyin CER(%) | Character CER(%) |
|---------------------|---------------|------------------|
| SPCI                | 4.54          | 9.85             |
| - PPGA              | 4.77          | 9.21             |
| - LWLI               | 5.23          | 9.74             |
| - Two-Stage Training| 7.39          | 13.90            |

Furthermore, similar to [20], we find that training directly from scratch to be unstable, which shows that two-stage training is essential. We attribute this to different difficulties and different loss ranges for pinyin and character when training from scratch. The advantage of the two-stage training method is that the dual-decoder model can get a better model initialization from separate models while speeding up convergence and model training.

### 5.3. Effect of hyperparameter $\lambda$

To analyze how weight $\lambda$ of the combined loss contributes to performance, we conduct an experiment. As is shown in Table 3, we find that the higher weight on the character side is more helpful. Because generating character transcripts is more difficult than generating pinyin transcripts, it is reasonable for the character side to have a higher weight. However, ignoring the pinyin side will harm the performance of the model. In this paper, we set $\lambda$ to be 0.5.

### 5.4. Compare proposed model to other models

Table 4 compares the proposed SPCI model to various mainstream end-to-end models. The experiments show that the SPCI model outperforms all the other models, including the plain Seq2Seq model without regularization, CTC-based LAS and attention-based LAS.

| Model          | CER(%) |
|----------------|--------|
| SPCI(Proposed) | -      | 9.85   |
| Seq2Seq [21]   | -      | 11.4   |
| LAS [22]       | -      | 10.56  |
| RNN-T [23]     | 10.13  | 11.82  |

### 6. CONCLUSION

In the paper, we propose a Mandarin Chinese ASR model, which is a layer-wise interactive dual-decoder structure based on Transformer utilizing the characteristics of the pinyin and character and an effective training method. The results on the test set of AISHELL-1 dataset show that the proposed model outperforms various related models and mainstream ASR models on AISHELL-1 dataset.
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