ONE IN A HUNDRED: SELECT THE BEST PREDICTED SEQUENCE FROM NUMEROUS CANDIDATES FOR STREAMING SPEECH RECOGNITION

Zhengkun Tian\textsuperscript{1,2}, Jiangyan Yi\textsuperscript{1}, Ye Bai\textsuperscript{1,2}, Jianhua Tao\textsuperscript{1,2,3}, Shuai Zhang\textsuperscript{1,2}, Zhengqi Wen\textsuperscript{1}

\textsuperscript{1}National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences, Beijing, China
\textsuperscript{2}School of Artificial Intelligence, University of Chinese Academy of Sciences, Beijing, China
\textsuperscript{3}CAS Center for Excellence in Brain Science and Intelligence Technology, Beijing, China

\section*{ABSTRACT}
The RNN-Transducers and improved attention-based sequence-to-sequence models are widely applied to streaming speech recognition. Compared with these two end-to-end models, the CTC model is more efficient in training and inference. However, it cannot capture the dependencies between the output tokens. We assume that we can pick out the best sequence among the first N candidates predicted by the CTC model. Enough number and enough diversity of candidates can compensate it for the lack of language modeling ability. Therefore, we improve the hybrid CTC and attention model, and introduce a two-stage inference method named one-in-a-hundred (OAH). During inference, we first generate many candidates by the CTC decoder in a streaming fashion. Then the transformer decoder selects the best candidate based on the corresponding acoustic encoded states. All the experiments are conducted on a Chinese Mandarin dataset AISHELL-1. The results show that our proposed model can implement stream decoding in a fast and straightforward way. Our model can achieve up to 20\% reduction in the character error rate than the baseline CTC model. In addition, our model can also perform non-streaming decoding.

\textbf{Index Terms}— Streaming Speech Recognition, End-to-End Models, Hybrid CTC and Attention, Two-Stage Inference, One-In-A-Hundred

1. INTRODUCTION

Streaming speech recognition has been applied to many real scenarios, like meeting real-time transcription and keyboard dictation systems on mobile phones. The mainstream models for streaming speech recognition include RNN-Transducer (RNN-T) models and the improved attention-based sequence-to-sequence models \cite{1,2,3,4,5,6,7}.

The RNN-T model, which utilizes unidirectional recurrent neural networks as the encoder, can be directly applied to streaming speech recognition \cite{8,9,10,11}. However, the RNN-T model suffers from the inefficiency of training and inference \cite{10,11}. The original attention-based sequence-to-sequence model decodes the output sequences based on the previously predicted tokens and the entire encoded acoustic states, which prevents it from decoding the output sequence in a streaming way \cite{7}. The improved attention-based sequence-to-sequence models mainly include the following types: the monotonic chunk-wise attention (MoChA) \cite{12}, the triggered attention \cite{4}, the continuous integrate-and-fire (CIF) \cite{13}, the synchronous transformer \cite{7}, and so on. These models utilize many tricky methods to segment the encoded states and then compute the attention weights on the segment states. Therefore, it is challenging and complicated to implement these improved attention-based models. As a kind of end-to-end model, connectionist temporal classification (CTC) models was first proposed to transcribe the acoustic feature sequences into the corresponding text sequence \cite{14,15,16}. The CTC model cannot capture the dependencies between the output tokens \cite{8}. Therefore, CTC models tend to be integrated with an external n-gram language model to improve performance. Recently, some very deep convolution CTC models, like Jasper \cite{17} and ContextNet \cite{18}, have achieved competitive performance with other end-to-end models. Although very deep convolution layers make the model able to model a very long-range context, it will also result in a large latency and prevent the model from being applied to streaming speech recognition.

The CTC model is more efficient in inference than the other two end-to-end models. We assume that we can pick out the best sequence from the first N candidates predicted by the CTC model. We can compensate the CTC model for the lack of language modeling ability by generating enough diversity and enough number of candidates. In this paper, we improve the hybrid CTC and attention model \cite{19}, and introduce a two-stage inference method named one-in-a-hundred (OAH) for streaming speech recognition. Our model consists of three components, a latency-controlled streaming transformer encoder, a CTC decoder, and a transformer decoder. We first make the self-attention mechanism in the transformer encoder focus on the local context to model the input sequence in a streaming fashion. Then we introduce a latency-controlled context layer at the top of the transformer encoder to model the future context of limited range. During training, these three components are optimized jointly. The one-in-a-hundred inference process can be divided into two stages: sampling and one-step scoring. At the sampling stage, the CTC decoder generates many possible sequences as candidates. At the one-step scoring stage, the transformer decoder scores all these candidates based on the corresponding acoustic encoded states and then select the sequence with the highest average score as the final predict sequence. All experiments are conducted on a public Chinese Mandarin dataset AISHELL-1. The results show that our proposed model can achieve up to 20\% reduction in the character error rate compared to the baseline CTC model. Furthermore, our model can also perform non-streaming decoding.

The remainder of this paper is organized as follows. We introduce the details of the model and related works in Section 2 and Section 3 respectively. Our experimental setup and results will be presented in Section 4. The conclusions and future works will be given in Section 5.
2. OUR PROPOSED METHOD

We improve the hybrid CTC and Attention model, as shown in Fig.1(a). Our model consists of three components, a latency-controlled streaming transformer encoder, a CTC decoder, and a transformer decoder.

2.1. Model Architecture

2.1.1. The Latency-Controlled Streaming Transformer Encoder

The transformer encoder generally consists of a convolutional down-sampling block, a positional embedding, and \( N \) transformer encoder blocks. The transformer encoder block is composed of a multi-head self-attention block and a feed-forward network layer \([20]\). The original transformer encoder depends on all context to compute the self-attention block and a feed-forward network layer \([20]\).

![Transformer Encoder Block](image)

The transformer encoder is the same as it in speech transformer \([21]\), which is composed of masked multi-head self-attention, multi-head cross-attention, feed-forward network and positional embedding. During training, the decoder adopts a triangle-like mask to mask force the decoder to focus on the previous tokens \([20]\). We compute the CTC loss \( L_{CTC} \) and the cross entropy loss \( L_{CE} \) with label smooth for the CTC decoder and transformer decoder respectively. These three components are optimized jointly. The joint loss is expressed as \( L_{Joint} \).

\[ L_{Joint} = \alpha L_{CTC} + (1 - \alpha) L_{CE} \]  (3)

where \( \alpha \) is the weight of \( L_{CTC} \).

On the other hand, inspired by DeepSpeech2 \([16]\), we put a latency-controlled context layer at the top of the encoder to model the fixed-range future context. The context layer is composed of a 1D convolution layer with kernel size \( \varepsilon + 1 \). The \( \varepsilon \) means the range of future context. The acoustic encoded states can be expressed as \( h_t \).

\[ h_t = \sum_{i=0}^{\varepsilon} w_i h_{t+i} + b_i \]  (2)

Where \( h \) is the output of the last streaming transformer encoder block. \( w \) and \( b \) indicate the weight and bias respectively. The latency can be express as \( 40 \times (\varepsilon + 1) \)ms, where 40ms means the convolutional down-sampling block can reduce the length of input sequences with frame shift 10ms by 4 times. With the latency-controlled context layer, the computation of ideal latency does not rely on the depth of the encoder.

2.1.2. The CTC Decoder and Transformer Decoder

The CTC decoder contains only a linear project layer, which is utilized to compute the label posterior probabilities of CTC. The transformer decoder is the same as it in speech transformer \([21]\), which is composed of masked multi-head self-attention, multi-head cross-attention, feed-forward network and positional embedding. During training, the decoder adopts a triangle-like mask to mask force the decoder to focus on the previous tokens \([20]\). We compute the CTC loss \( L_{CTC} \) and the cross entropy loss \( L_{CE} \) with label smooth for the CTC decoder and transformer decoder respectively. These three components are optimized jointly. The joint loss is expressed as \( L_{Joint} \).

\[ L_{Joint} = \alpha L_{CTC} + (1 - \alpha) L_{CE} \]  (3)

where \( \alpha \) is the weight of \( L_{CTC} \).
2.2. Inference

We introduce two-stage inference method named one-in-a-hundred for streaming inference, as shown in Fig.1(c). The inference process can be split into two stages: sampling and one-step scoring. At the sampling stage, the CTC decoder can generate $N$ candidate sequences by prefix beam search [22]. The number of candidates is equal to the width of beams. At the one-step scoring stage, the transformer decoder scores all the candidates. Different from the language model rescoring, the one-step scoring relies on the corresponding acoustic encoded states to match the selected candidate with the pronunciation. Due to the transformer decoder can perform parallel computation, the scoring can be finished in one-step, which improve the efficiency of inference. As long as the candidates are diverse enough, we might be able to pick out the best one. The score of a sentence of length $L$ can be expressed as

$$S_{y_{1:L}} = \text{OneStepScoring}(y_{1:L}, h_{enc}) \ast 1/L$$

(4)

where $h_{enc}$ means the corresponding acoustic encoded states. We apply length normalization to the scoring process to prevent the model from tending to select the short candidate as the predicted sequence.

In addition, our model support two inference mode, streaming and non-streaming. When we adopt the CTC decoder as the leading role and the transformer decoder to score the candidates generated by the CTC decoder, the model can perform the streaming inference. The process is name one-in-a-hundred. From another viewpoint, when we make the transformer decoder as the leading role and the CTC decoder as the assistant, the transformer decoder can still model the whole context and decode in a non-streaming fashion [19]. The non-streaming decoding process starts with the beginning token $<$S$>$/$<$E$>$. At every step, we interpolate the scores of two decoders. The model will repeat the above process until the end-of-sentence token is predicted.

3. RELATED WORKS

The most similar to our work is the two-pass end-to-end model [23], which combines the RNN-T and LAS decoder. Compared with the two-pass end-to-end model, we combine the CTC model and transformer. The CTC model is more efficient in training and inference. Therefore, we can generate hundreds of candidate sequences and evaluate them in a very short time. For the RNN-T model, it is very challenging to generate many candidates by beam search during inference, which will cost plenty of time and memory. As well known, the RNN-T is more powerful to model the language. Therefore, our motivation is to compensate the CTC models for the lack of language modeling ability by picking out the best sequence from the various candidates.

Triggered attention model [4] is a kind of the hybrid CTC and attention model for streaming speech recognition, which utilizes the spike-like posterior probabilities generated by CTC to segment the encoded states. Our model can be regarded as an improved CTC model, which utilizes the attention-based decoder to evaluate the results of the CTC decoder. What’s more, our model support two inference mode, streaming and non-streaming.

| CTC Weight $\alpha$ | Dev | Test |
|---------------------|-----|------|
| 0.1                 | 8.22| 6.92 |
| 0.2                 | 8.26| 7.04 |
| 0.3                 | 8.31| 7.14 |
| 0.5                 | 8.89| 7.55 |
| 0.7                 | 9.53| 8.03 |
| 1.0                 | 8.88| -    |

Table 1. Comparison of models with different CTC weights (CER %).

4. EXPERIMENTS AND RESULTS

4.1. Dataset

In this work, all experiments are conducted on a public Mandarin speech corpus AISHELL-1. The training set contains about 150 hours of speech (120,098 utterances) recorded by 340 speakers. The development set contains about 20 hours (14,326 utterances) recorded by 40 speakers. And about 10 hours (7,176 utterances / 36109 seconds) of speech is used as the test set. The speakers of different sets are not overlapped.

4.2. Experimental Setup

For all experiments, we use 40-dimensional FBank features computed on a 25ms window with a 10ms shift. We choose 4233 characters (including a padding symbol $<$PAD$>$, an unknown symbol $<$UNK$>$, and an start-or-end-of-sentence symbol $<$S$>$/$<$E$>$) as modeling units.

Our model consists of 12 encoder blocks and 12 decoder blocks. There are 4 heads in multi-head attention. The 2D convolution front end utilizes two-layer time-axis CNN with ReLU activation, stride size 2, channels 320, and kernel size 3. Both the output size of the multi-head attention and the feed-forward layers are 512. The hidden size of feed-forward layers is 768. The range of the self-attention in streaming transformer encoder blocks is limited from 10 frames on the left to the current position ($\tau = 10$). We adopt an Adam optimizer with warmup steps 12000 and the learning rate scheduler reported in [20]. After 100 epochs, we average the parameters saved in the last 30 epochs. We also use the time mask and frequency mask method proposed in [23] instead of speed perturbation.

We use the character error rate (CER) to evaluate the performance of different models. For evaluating the inference speed of different models, we decode utterances one by one to compute real-time factor (RTF) on the test set. The RTF is the time taken to decode one second of speech. All experiments are conducted on a GeForce GTX TITAN X 12G GPU.

4.3. Results

4.3.1. Comparison of models with different CTC weights

We first compare the models with different CTC weights. We set the range of future context in latency-controlled context layer to 10 and adopt beam search with width 10 during inference. We evaluate the CER on the development and test set in two ways, which are one-pass CTC decode (without OAH) and two-pass decode (with OAH).

---

1 The code of prefix beam search is available at https://github.com/PaddlePaddle/DeepSpeech/tree/develop/decoders

2 https://openslr.org/33/

3 Our code will be released in https://github.com/ZhengkunTian/OneInAHundred
As shown in Table 1, the model with CTC weight 0.1 can achieve the best performance on development and test test. Furthermore, it’s obvious that applying our OAH strategy can generally improve the performance of the model. However, with the increase of CTC weight, the performance of the model gradually deteriorated. We assume that the weight $\alpha$ can balance the importance of the CTC model in the training process. An inappropriate weight will make the model unbalanced in the training process, leading to the decline of model performance. When the weight $\alpha$ is 1.0, the transformer decoder is discarded. Under this condition, the model can be regarded as a CTC model. By contrast, we find that the joint training with an appropriate weight can improve performance.

### 4.3.2. Comparison of models with different ranges of future context

We evaluate the models with different range $\varepsilon$ of future context in Table 2. We set the CTC weight of all models to 0.1 and adopt the beam search with width 10 during inference. The latency is proportional to the range of future context. It can be calculated by $40 \times (\varepsilon + 1)$ ms. It appears that the more future information the model focuses on, the better performance it achieves. Meanwhile, it will increase the computation and the real-time rate. When the range $\varepsilon$ is set to 10 and 20, there is no significant difference in the performance. Considering that the model focuses on the next 10 frames can achieve lower latency and faster inference speed, we set the range of future context to 10 in subsequent experiments.

### 4.3.3. Comparison of the model with different beam widths

We choose the model with the CTC weight 0.1 and the future context range 10 to conduct these experiments in Table 3. The results show that the beam widths have little effect on the performance of the CTC decode results (without OAH). We assume that the CTC part of our model has learned a very sharp posterior probability distribution, which leads to a numerous difference between the probabilities of search paths. However, the beam width plays a vital role in our two-stage inference method. The model with OAH scoring can achieve up to 20% reduction in CER compared to the performance of the base CTC model (without OAH). We assume that the CTC part of our model has learned a very sharp posterior probability distribution, which leads to a numerous difference between the probabilities of search paths. However, the beam width plays a vital role in our two-stage inference method. The model with OAH scoring can achieve up to 20% reduction in CER compared to the performance of the base CTC model (without OAH). The beam widths are equal to the number of candidate sequences. The larger the beam width, the better performance the model achieves. The model with beam width 50 achieves a CER of 7.41% and an RTF of 0.0380. When the width is larger than 50, the performance will decline. We suspect that the best sequence may exist in the first 50 candidates. Too many candidates may confuse the transformer decoder during one-step scoring. Too few candidates will make the model miss the best sequence.

### 4.3.4. Comparison with other models

We also compare our model with other models. As shown in Table 4, our model with OAH can achieve a comparable performance with TDNN-Chain model [25] and ST-NAT [26]. What’s more, our model has a real-time factor of 0.0380, which exceeds SA-Transducer [6], Sync-Transformer [7], and speech-transformer [21].

Our model with OAH achieves better performance compared to the CTC with language rescoring. The language rescoring leads to the performance degradation. We think that the language rescoring evaluates the candidates without relying on acoustic information, which results in the output sequence mismatch with the true pronunciation.

In addition, our model is able to decoding the output sequence in a non-streaming fashion (NS). Under this condition, our model achieves a CER of 7.05%. Compared with the speech-transformer with the same parameters configuration, our model has a little performance degradation.

### 5. CONCLUSIONS AND FUTURE WORKS

In this paper, we improve the hybrid CTC and attention model and introduce a two-stage inference method named one-in-a-hundred (OAH). Our proposed model consists of three components, a latency-controlled streaming transformer encoder, a CTC decoder, and a transformer decoder. The latency-controlled streaming transformer encoder can model the streaming input feature sequence in very low latency. The streaming inference process can be split into two stages: sampling and one-step scoring. At the first stage, the CTC decoder can generate up to a hundred candidate sequences quickly. At the second stage, the transformer decoder score all the candidate sequences based on the corresponding acoustic encoded states in one step. We can make up the weakness that the CTC model can’t model the dependencies between the output tokens by keeping the diverse candidates. We conduct the experiments on a public Chinese mandarin dataset AISHELL-1. The results show
that our proposed method can achieve up to 20% reduction in CER compared to the baseline CTC model. What’s more, our model also can perform non-streaming decoding with a little performance degradation.

In the future, we will improve the model in two aspects. On the one hand, we will explore how to generate numerous candidates in a faster fashion. On the other hand, we will try our best to unify the streaming and non-streaming models into this framework without any performance degradation.

6. REFERENCES

[1] Navdeep Jaitly, David Sussillo, Quoc V Le, Oriol Vinyals, Ilya Sutskever, and Samy Bengio, “A neural transducer,” arXiv preprint arXiv:1511.04868, 2015.

[2] Tara N Sainath, Chung-Cheng Chiu, Rohit Prabhavalkar, Anjuli Kannan, Yonghui Wu, Patrick Nguyen, and ZhiJeng Chen, “Improving the performance of online neural transducer models,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 5864–5868.

[3] Yanzhang He, Tara N Sainath, Rohit Prabhavalkar, Ian McGraw, Raziel Alvarez, Ding Zhao, David Rybach, Anjuli Kannan, Yonghui Wu, Ruoming Pang, et al., “Streaming end-to-end speech recognition for mobile devices,” arXiv: Computation and Language, 2018.

[4] Niko Moritz, Takaaki Hori, and Jonathan Le Roux, “Triggered attention for end-to-end speech recognition,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 5666–5670.

[5] Linhao Dong and Bo Xu, “Cif: Continuous integrate-and-fire for end-to-end speech recognition,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 6079–6083.

[6] Zhengkun Tian, Jiayuan Yi, Jiuhua Tao, Ye Bai, and Zhengqi Wen, “Self-Attention Transducers for End-to-End Speech Recognition,” in Proc. Interspeech 2019, 2019, pp. 4395–4399.

[7] Zhengkun Tian, Jiayuan Yi, Ye Bai, Jiuhua Tao, Shuai Zhang, and Zhengqi Wen, “Synchronous transformers for end-to-end speech recognition,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 7884–7888.

[8] Alex Graves, “Sequence transduction with recurrent neural networks,” arXiv preprint arXiv:1211.3711, 2012.

[9] Alex Graves, Abdel-rahman Mohamed, and Geoffrey Hinton, “Speech recognition with deep recurrent neural networks,” in 2013 IEEE international conference on acoustics, speech and signal processing. IEEE, 2013, pp. 6645–6649.

[10] Tom Bagby, Kanishka Rao, and Khe chai sim, “Efficient implementation of recurrent neural network transducer in tensor-flow,” in 2018 IEEE Spoken Language Technology Workshop (SLT). IEEE, 2018, pp. 506–512.

[11] Jinyu Li, Rui Zhao, Hu Hu, and Yifan Gong, “Improving rnn transducer modeling for end-to-end speech recognition,” arXiv: Computation and Language, 2019.

[12] Chung-Cheng Chiu and Colin Raffel, “Monotonic chunkwise attention,” arXiv preprint arXiv:1712.05382, 2017.

[13] Linhao Dong and Bo Xu, “Cif: Continuous integrate-and-fire for end-to-end speech recognition,” arXiv preprint arXiv:1905.11235, 2019.

[14] 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. ACM, 2006, pp. 369–376.

[15] Awni Hannun, Carl Case, Jared Casper, Bryan Catanzaro, Greg Diamos, Erich Elsaen, Ryan Prenger, Sanjeev Satheesh, Shubho Sengupta, Adam Coates, et al., “Deep speech: Scaling up end-to-end speech recognition,” arXiv preprint arXiv:1412.5567, 2014.

[16] Dario Amodei, Sundaram Ananthanarayanan, Rishita Anubhai, Jingliang Bai, Eric Battenberg, Carl Case, Jared Casper, Bryan Catanzaro, Qiang Cheng, Guoliang Chen, et al., “Deep speech 2: End-to-end speech recognition in english and mandarin,” in International conference on machine learning, 2016, pp. 173–182.

[17] Jason Li, Vitaly Lavrukhin, Boris Ginsburg, Ryan Leary, Oleksii Kuchaiev, Jonathan M Cohen, Huyen Nguyen, and Ravi Teja Gadde, “Jasper: An end-to-end convolutional neural acoustic model,” arXiv preprint arXiv:1904.03288, 2019.

[18] Wei Han, Zhengdong Zhang, Yu Zhang, Jiuhui Yu, Chung-Cheng Chiu, James Qin, Anmol Gulati, Ruoming Pang, and Yonghui Wu, “Contextnet: Improving convolutional neural networks for automatic speech recognition with global context,” arXiv preprint arXiv:2005.03191, 2020.

[19] Shinji Watanabe, Takaaki Hori, Suyoun Kim, John R Hershey, and Tomoki Hayashi, “Hybrid ctc/attention architecture for end-to-end speech recognition,” IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 8, pp. 1240–1253, 2017.

[20] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin, “Attention is all you need,” in Advances in Neural Information Processing Systems, 2017, pp. 5998–6008.

[21] Linhao Dong, Shuang Xu, and Bo Xu, “Speech-transformer: a no-recurrence sequence-to-sequence model for speech recognition,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 5884–5888.

[22] Awni Y Hannun, Andrew L Maas, Daniel Jurafsky, and Andrew Y Ng, “First-pass large vocabulary continuous speech recognition using bi-directional recurrent dnns,” arXiv preprint arXiv:1408.2873, 2014.

[23] Tara N Sainath, Ruoming Pang, David Rybach, Yanzhang He, Rohit Prabhavalkar, Wei Li, Mirko Visontai, Qiao Liang, Trevor Strohman, Yonghui Wu, et al., “Two-pass end-to-end speech recognition,” arXiv preprint arXiv:1908.10992, 2019.

[24] Daniel S Park, William Chan, Yu Zhang, Chung-Cheng Chiu, Barret Zoph, Ekin D Cubuk, and Quoc V Le, “Specaugment: A simple data augmentation method for automatic speech recognition,” arXiv preprint arXiv:1904.08779, 2019.

[25] Daniel Poevy, Vijayaditya Peddinti, Daniel Galvez, Pegah Ghahremani, Vimal Manohar, Xingyu Na, Yiming Wang, and Sanjeev Khudanpur, “Purely sequence-trained neural networks for asr based on lattice-free mmi,” in Interspeech, 2016, pp. 2751–2755.
[26] Zhengkun Tian, Jiangyan Yi, Jianhua Tao, Ye Bai, Shuai Zhang, and Zhengqi Wen, “Spike-triggered non-autoregressive transformer for end-to-end speech recognition,” *arXiv preprint arXiv:2005.07903*, 2020.

[27] Julian Salazar, Katrin Kirchhoff, and Zhiheng Huang, “Self-attention networks for connectionist temporal classification in speech recognition,” in *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2019, pp. 7115–7119.