



# Phonetic-assisted Multi-Target Units Modeling for Improving Conformer-Transducer ASR system

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## Abstract

Exploiting effective target modeling units is very important and has always been a concern in end-to-end automatic speech recognition (ASR). In this work, we propose a phonetic-assisted multi-target units (PMU) modeling approach, to enhance the Conformer-Transducer ASR system in a progressive representation learning manner. Specifically, PMU first uses the pronunciation-assisted subword modeling (PASM) and byte pair encoding (BPE) to produce phonetic-induced and text-induced target units separately; Then, three new frameworks are investigated to enhance the acoustic encoder, including a basic PMU, a paraCTC and a paCTC, they integrate the PASM and BPE units at different levels for CTC and transducer multi-task training. Experiments on both LibriSpeech and accented ASR tasks show that, the proposed PMU significantly outperforms the conventional BPE, it reduces the WER of LibriSpeech clean, other, and six accented ASR testsets by relative 12.7%, 4.3% and 7.7%, respectively.

**Index Terms:** multi-target units, PMU, paCTC, Conformer-Transducer, end-to-end ASR

## 1. Introduction

The Conformer-Transducer (ConformerT) has achieved state-of-the-art results in many ASR tasks [1–4] because of its perfect inheritance of the advantages of conformer and transducer. It captures both local and global features by combining the convolution module and transformer in a parameter-efficient way. Together with the natural streaming property of transducer, ConformerT has become increasingly appealing in recent end-to-end (E2E) ASR systems.

As many E2E ASR systems, exploring effective target modeling units for ConformerT is also very crucial. The main types of E2E ASR target units can be divided into the text-induced units and phonetic-induced ones. The character, word and subword are all text-induced units and have been extensively studied [5–10]. Compared with character, subword can avoid too long output sequence and dependency, which reduces the difficulty of modeling and decoding [7]. Many subword modeling techniques have been proposed: the byte pair encoding (BPE) [11], WordPieceModel (WPM) [12] and unigram language model (ULM) [13], etc. However, all of these techniques are purely text-induced without any access to the underlying phonetic/pronunciation information which is the key of ASR. The syllable, phoneme [5, 6, 14, 15] belong to the phonetic-induced target units, they enable the model to learn better pho-

netic patterns of a language, however, an additional pronunciation lexicon is required during both model training and inference. Therefore, how to well exploit the information in both text-induced and phonetic-induced target units become very important and fundamental.

In the literature, several recent works have been proposed to combine the text and phonetic information for building better E2E ASR system. Such as, [16] proposed a hybrid target unit of syllable-char-subword in a joint CTC/Attention multi-task learning for the Mandarin ASR system; While in [17], a pronunciation assisted subword modeling (PASM) was introduced to extract ASR target units by exploring their acoustic structure from the pronunciation lexicon. In addition, [18] tried to exploit the text and underlying phonetic information in acoustics in another way, the authors used a set of hierarchically increasing text units to the CTC modeling of intermediate Transformer encoder layers. All these works have been verified to be effective for improving current E2E ASR systems.

Motivated by the PASM and work in [18], this study aims to improve the Conformer-Transducer ASR system by proposing a phonetic-assisted multi-target units modeling (PMU) approach. The PMU is designed to learn information from both the phonetic-induced PASM and text-induced BPE units, using three new acoustic modeling frameworks as follows: 1) Basic PMU. The ConformerT is trained with both CTC and transducer losses, but assigning PASM and BPE units to them respectively; 2) paraCTC. With the same BPE units as in 1) for transducer, a parallel CTC loss with both PASM and BPE as Conformer encoder's target units is taken as the auxiliary task of ConformerT model training; 3) paCTC. Different from 1) and 2), paCTC adopts a phonetic conditioned acoustic encoder, by using the PASM and BPE units in an interactive manner to the CTC loss of different intermediate Conformer encoders. From the experiments that conducted on LibriSpeech and Common-Voice datasets, we see that the standard ConformerT is significantly improved by our proposed PMU, up to relative 4.3% to 12.7% WER reductions are achieved on the LibriSpeech clean and other, or the six accented English test sets of Common-Voice.

## 2. Conformer-Transducer

The Conformer-Transducer (ConformerT) was first proposed in [1, 2]. It can be trained using the end-to-end RNN-T loss [19] with a label encoder and a Conformer-based acoustic encoder (AEncoder). The architecture is illustrated in Fig.1 (a). Given an input acoustic feature with  $T$  frames as  $\mathbf{x} = (\mathbf{x}_1, \dots, \mathbf{x}_T)$ , and its transcription label sequence of length  $U$  as  $\mathbf{y} = (y_1, \dots, y_U)$ . The AEncoder first transforms  $\mathbf{x}$  into a high representation  $h_t, t \leq T$ , and the label encoder, acting as a language model,

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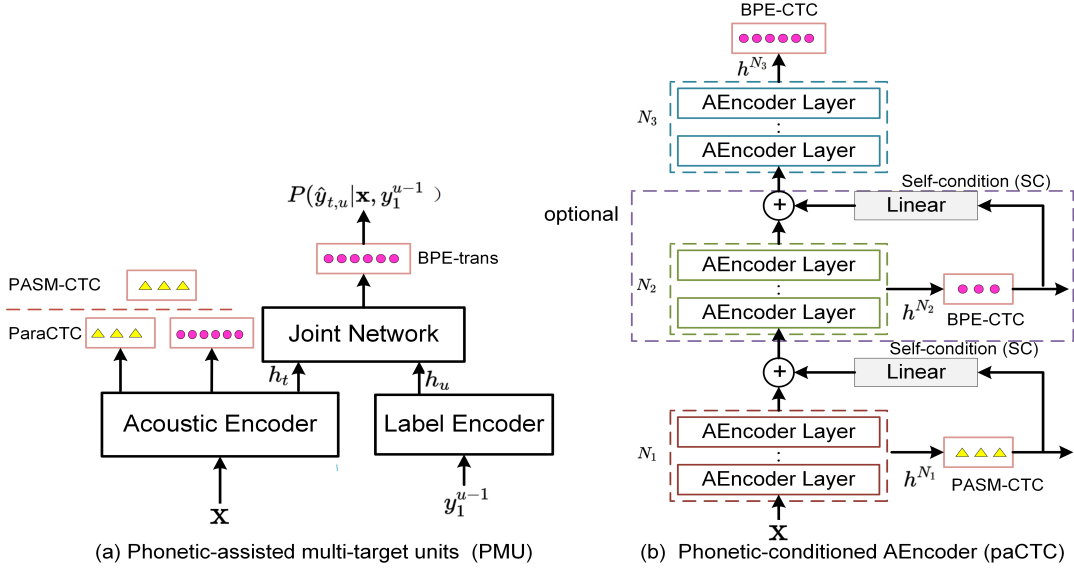


Figure 1: Structure of (a) the proposed phonetic-assisted multi-target units (PMU) and (b) its phonetic-conditioned AEncoder (paCTC).

produces a representation  $h_u$  given its previous emitted label sequence  $y_1^{u-1}$ . Then,  $h_t$  and  $h_u$  are combined using the joint network composed of feed-forward layers and a non-linear function to compute output logits. Finally, by applying a Softmax to the output logits, we can produce the distribution of current target probabilities as:

$$P(\hat{y}_{t,u}|\mathbf{x}, y_1^{u-1}) = \text{Softmax}(\text{Joint}(h_t, h_u)) \quad (1)$$

The label  $\hat{y}_{t,u}$  can optionally be blank symbol. Removing all the blank symbols in  $\hat{y}_{t,u}$  sequence yields  $\mathbf{y}$ . Given  $\mathcal{A}$ , the set of all possible alignments  $\hat{\mathbf{y}}$  (with blank symbols  $\phi$ ) between input  $\mathbf{x}$  and output  $\mathbf{y}$ , ConformerT loss function can be computed as the following negative log posterior:

$$\mathcal{L}_{\text{trans}} = -\log P(\mathbf{y}|\mathbf{x}) = -\log \sum_{\hat{\mathbf{y}} \in \mathcal{A}} P(\hat{\mathbf{y}}|\mathbf{x}) \quad (2)$$

Besides the transducer loss  $\mathcal{L}_{\text{trans}}$ , as in [20], we also jointly train ConformerT with an auxiliary CTC loss  $\mathcal{L}_{\text{CTC}}$  [21] to learn frame-level acoustic representations and provide supervision to the AEncoder. The overall ConformerT objective function is defined as:

$$\mathcal{L}_{\text{obj}} = \lambda_{\text{trans}} \mathcal{L}_{\text{trans}} + \lambda_{\text{ctc}} \mathcal{L}_{\text{CTC}} \quad (3)$$

where  $\lambda_{\text{trans}}, \lambda_{\text{ctc}} \in [0, 1]$  are tunable loss weights.

### 3. Proposed Methods

Although the PASM [17] has been proposed to enhance the extraction of E2E ASR target units, by leveraging the phonetic structure of acoustics in speech using a pronunciation lexicon, most current ConformerT ASR systems still only use the purely text-induced subwords, such as BPEs, wordpieces as their target modeling units [2, 3]. This may be constrained by the phonetic pattern in lexicon, PASM tends to produce short subwords and avoids modeling larger or full-words with single tokens, the resulting relative small vocabulary size greatly limits the performance upper bound of PASM. Therefore, in this study, we propose a phonetic-assisted multi-target units (PMU) modeling to integrate the advantages of both PASM and BPE units for

improving ConformerT in a CTC/transducer multi-task training framework.

The whole architecture of ConformerT with PMU is demonstrated in Fig.1(a), where we use different types of target units for the CTC and transducer branch. The BPE-trans means using text-induced BPE units to align the transducer outputs during ConformerT training, while for the shared acoustic encoder (AEncoder) with CTC branch, we investigate three new target units modeling methods, as illustrated in the left part of Fig.1(a) and Fig.1(b), the first one is the basic PMU with PASM-CTC, where only PASM units are taken as the CTC targets, the other two replace PASM-CTC with a paraCTC and a paCTC separately. All the PASM-CTC, BPE-CTC and BPE-trans are composed of a single fully-connected feed-forward layer with different target units followed by Softmax function. Given both PASM and BPE units, the overall objective loss of basic PMU is defined as,

$$\mathcal{L}_{\text{PMU}} = \lambda_{\text{trans}} \mathcal{L}_{\text{BPE-trans}} + \lambda_{\text{ctc}} \mathcal{L}_{\text{PASM-CTC}} \quad (4)$$

Where  $\mathcal{L}_{\text{BPE-trans}}$  and  $\mathcal{L}_{\text{PASM-CTC}}$  represent the loss of transducer and CTC using BPE and PASM units as their targets, respectively. If we use paraCTC or paCTC, the loss of  $\mathcal{L}_{\text{PASM-CTC}}$  in Eq.(4) will be replaced by their corresponding CTC loss  $\mathcal{L}_{\text{paraCTC}}$  and  $\mathcal{L}_{\text{paCTC}}$ , respectively. The details of how to produce PASM units with a given pronunciation lexicon and training texts can be found in [17].

#### 3.1. ParaCTC

Training a model with CTC loss applied in parallel to the final layer has recently achieved success [22–25]. In our paraCTC, as shown in Fig.1(a), we use two different linear layers to transform the AEncoder representation to BPE and PASM units with  $\mathcal{L}_{\text{CTC}}(\mathbf{y}_{\text{BPE}}|\mathbf{x})$  and  $\mathcal{L}_{\text{CTC}}(\mathbf{y}_{\text{PASM}}|\mathbf{x})$  loss, respectively. The overall loss function of paraCTC is defined as,

$$\mathcal{L}_{\text{paraCTC}} = \alpha \mathcal{L}_{\text{CTC}}(\mathbf{y}_{\text{PASM}}|\mathbf{x}) + (1 - \alpha) \mathcal{L}_{\text{CTC}}(\mathbf{y}_{\text{BPE}}|\mathbf{x}) \quad (5)$$

where  $\alpha \in (0, 1)$ ,  $\mathbf{y}_{\text{PASM}}$  and  $\mathbf{y}_{\text{BPE}}$  represent the target units of CTC is PASM and BPE respectively. With Eq.(5), the underlying phonetic and text structure information in PASM and BPE are effectively exploited and combined to boost the AEncoder.

### 3.2. PaCTC

Different from basic PMU and paraCTC, our proposed paCTC enhances the AEncoder in a phonetic-conditioned manner, by using the CTC alignments between  $y_{\text{PASM}}$  or  $y_{\text{BPE}}$  and the output of intermediate AEncoder layers. The overview structure of paCTC is shown in Fig.1(b). We first cut the whole AEncoder into the lower  $N_1$  and top  $N_3$  layers. Then, the PASM-CTC and BPE-CTC joint training are applied to these two AEncoder blocks for aligning their frame-level outputs  $h^{N_1}$  and  $h^{N_3}$  respectively, using their corresponding loss of  $\mathcal{L}_{\text{PASM-CTC}}^{N_1}$  and  $\mathcal{L}_{\text{BPE-CTC}}^{N_3}$  as,

$$\mathcal{L}_{\text{paCTC}} = \beta \mathcal{L}_{\text{PASM-CTC}}^{N_1} + (1 - \beta) \mathcal{L}_{\text{BPE-CTC}}^{N_3} \quad (6)$$

Where  $\mathcal{L}_{\text{paCTC}}$  is the total paCTC loss and  $\beta \in (0, 1)$  is a weight parameter.

Moreover, as illustrated in Fig.1(b), a self-condition(SC) mechanism [26] is applied to further improve the AEncoder, by making the subsequent AEncoder layers conditioned on both the previous layer representation and the intermediate CTC predictions. The Linear in SC means using a fully-connected layer to linearly transform the dimension of intermediate CTC predictions to the same dimension of AEncoder layers. We expect paCTC can outperform the other two PMU variants, because it integrates both PASM and BPE advantages in a more effective way, by applying PASM-CTC on lower AEncoder enables ConformerT to learn better acoustic representations from the phonetic-induced PASM modeling, while applying BPE-CTC on the top AEncoder helps to produce more robust linguistic embeddings.

In addition, inspired by the idea of hierarchically increasing subword units in [18], we also design an optional structure (dashed block in Fig.1) in paCTC, by inserting an intermediate BPE-CTC alignment at the middle AEncoder block with  $N_2$  layers. With this optional structure, Eq.(6) is then modified as follows:

$$\mathcal{L}_{\text{paCTC}} = \frac{\beta}{2} \left( \mathcal{L}_{\text{PASM-CTC}}^{N_1} + \mathcal{L}_{\text{BPE-CTC}}^{N_2} \right) + (1 - \beta) \mathcal{L}_{\text{BPE-CTC}}^{N_3} \quad (7)$$

where  $\mathcal{L}_{\text{BPE-CTC}}^{N_2}$  is the BPE-CTC loss of intermediate middle AEncoder block. It's worth noting that the intermediate BPE-CTC and PASM-CTC have the same vocabulary size that is much smaller than the one of BPE-CTC applied to the top AEncoder block, such as 194 versus 3000. This paCTC with optional structure can not only leverage low-level phonetic information to produce better high-level linguistic targets, but also achieve a progressive representation learning process which can integrate different types of subwords in a fine-to-coarse manner. What's more, we explore two different variants of paCTC with optional structure, namely paCTC-s and paCTC-us. paCTC-s means we not only share two SC linear layers, but also share the linear layer parameters of both PASM-CTC and intermediate BPE-CTC, while paCTC-us means not.

## 4. Experiments and Results

### 4.1. Datasets

Our experiments are performed on two open-source English ASR tasks, one is the LibriSpeech dataset [27] with 100hrs training data and its clean and other test sets, the other is an accented ASR task with data selected from CommonVoice corpus [28]. Our accented English training data has 150 hours (hrs) of speech, including Indian, US and England accents and each with 50 hrs. We construct six test sets to evaluate the proposed methods for accented ASR, including three in-domain

tests with 2 hrs US, 1.92 hrs England and 3.87 hrs Indian accent speech, three out-of-domain test sets with 2 hrs Singapore, 2.2 hrs Canada and 2 hrs Australia accent speech.

### 4.2. Experimental Setup

All our experiments are implemented using library from the end-to-end speech recognition toolkit ESPnet [29]. We use global mean-variance normalized 80-dimensional log-mel filterbank as input acoustic features. No data augmentation techniques and no extra language model are applied.

For the acoustic encoder of ConformerT, we sub-sample the input features by a factor of 4 using two 2D-convolutional layers, followed by 12 conformer encoder layers with 2048 feed-forward dimension and 512 attention dimension with 8 self-attention heads. For the label encoder, we only use a 512-dimensional LSTM. The joint network is a 640-dimensional feed-forward network with tanh activation function. The warmup is set to 25000, and both label smoothing [30] weight and dropout is set to 0.1 for model regularization. The BPE units are generated by SentencePiece [31], and fast\_align [32] is used to produce PASM units with the CMU pronunciation lexicon<sup>1</sup>. In Table 1 and Table 2,  $\beta$  is set to 0.5 and 0.7, respectively,  $\alpha = 0.7$  for the paraCTC,  $\lambda_{\text{trans}} = \lambda_{\text{ctc}} = 0.5$  for all the systems with paCTC. All the system performances are evaluated using word error rates (WER (%)).

### 4.3. Results

#### 4.3.1. Results on Librispeech

Table 1: WER(%) on the clean and other test sets of Libri-100hrs ASR task.  $TU_{\text{ctc}}$  and  $TU_{\text{trans}}$  represent the type of target units for CTC and transducer in ConformerT, respectively. In paCTC, system 9-10 use the optional structure with  $N_1 = N_2 = N_3 = 4$ , while system 8 does not ( $N_2 = 0, N_1 = N_3 = 6$ ).

ID	Methods	$TU_{\text{ctc}}$	$TU_{\text{trans}}$	Evaluation	
				Clean	Other
1	ConformerT	BPE-194		11.2	30.6
2		BPE-3000		11.0	29.9
3		PASM-194		10.5	30.5
4	PMU	PASM-194	BPE-194	10.2	30.0
5		BPE-194	PASM-194	10.7	30.2
6		PASM-194	BPE-3000	10.1	28.4
7		paraCTC	BPE-3000	9.8	28.4
8		paCTC	BPE-3000	9.7	28.4
9		paCTC-s	BPE-3000	9.7	<b>28.3</b>
10	paCTC-us	BPE-3000	<b>9.6</b>	28.6	

We first examine our proposed methods on the clean and other test sets of Librispeech ASR task. Results are shown in Table 1. System 1 to 3 are our ConformerT baselines, each with its both CTC and transducer branches using a single type of target units. 'BPE/PASM-\*' means using BPE or PASM units with different vocabulary size. In our extensive experiments, we find 194 and 3000 are the best setups for PASM and BPE on the Libri-100hrs dataset, respectively. 'BPE-194' is used to make a fair comparison with 'PASM-194'. System 4-10 are the ConformerT models trained using our proposed PMU framework with three different variants: the basic PMU (system 4-6), PMU with paraCTC (system 7) and PMU with different structure of paCTC (system 8-10).

<sup>1</sup><http://www.speech.cs.cmu.edu/cgi-bin/cmudict>

Table 2: WER(%) on the in-domain and out-of-domain test sets on accented CommonVoice ASR task. In the paCTC, setup 9-10 use the optional structure, while setup 7-8 do not.

ID	Methods	TU <sub>ctc</sub>	TU <sub>trans</sub>	In-domain			Out-of-domain			Overall
				England	Indian	US	Australia	Canada	Singapore	
1	ConformerT	BPE-3000		21.9	26.8	18.7	24.1	17.1	35.4	24.4
2		BPE-205		21.7	25.0	17.6	24.5	16.2	33.8	23.4
3		PASM-205		21.6	24.7	17.8	24.6	16.6	35.1	23.9
4	PMU	PASM-205	BPE-205	21.4	24.7	17.8	23.7	16.3	33.7	23.2
5		BPE-205	PASM-205	21.9	24.9	17.8	24.4	16.1	33.7	23.4
6		paraCTC	BPE-205	21.3	24.7	17.3	24.0	16.2	33.1	23.1
7		paCTC	BPE-205	20.5	24.1	16.5	23.3	15.3	32.6	22.4
8		paCTC	BPE-3000	19.6	24.0	16.6	22.5	15.2	32.3	22.1
9		paCTC-s	BPE-3000	19.9	23.6	16.4	<b>22.0</b>	15.4	<b>31.3</b>	21.8
10		paCTC-us	BPE-3000	<b>19.8</b>	<b>23.1</b>	<b>15.8</b>	22.5	<b>14.8</b>	31.4	<b>21.6</b>

Comparing results of system 1-3 in Table 1, we see there is no big difference performance gap between using phonetic-induced PASM and text-induced BPE as their both CTC/transducer target units. PASM achieves the best result on the clean test set, while BPE obtains the best one on the other test set. However, when the proposed PMU modeling methods are applied, both WERs on the clean and other test sets are greatly reduced. When comparing the results of ConformerT with conventional BPE-3000 (system 2), even with the basic PMU, system 6 still achieves relative 8.2% and 5.0% WER reductions on the clean and other sets, respectively. Meanwhile, by comparing system 4 to 6, it’s clear that using PASM as CTC alignments, while larger BPE units as transducer targets is the best setup for basic PMU, it may due to the fact that, the clear phonetic correspondence of target units is critical for such time synchronous model. When comparing system 6 with 7-10, we see continuous WER reduction on the clean test set, even the performance improvement on the other set is limited. Finally, the paCTC-us achieves the best results on the clean testset. Compared with the best baseline (system 2), system 10 achieves 12.7% and 4.3% relative WER reduction on clean and other test set, respectively.

Table 3: WER(%) on Libri-100hrs clean and other test sets for PMU with paCTC (Fig.1 (b), Eq.(6)) without optional structure under different setup conditions. Setup 4 means replacing the PASM-CTC with BPE-194 CTC at  $N_1$  layers.

ID	#layer		$\beta$	Evaluation	
	$N_1$	$N_3$		Clean	Other
1	6	6	0.3	9.8	<b>28.0</b>
2	6	6	0.5	<b>9.7</b>	28.4
3	6	6	0.7	10.0	28.6
4	6	6	0.5, BPE-194	10.0	29.4
5	3	9	0.5	10.3	30.1
6	9	3	0.5	9.8	28.6

In fact, before we propose the paCTC with optional structure, we perform a set of parameter tuning experiments to see how they affect the paCTC performance. Results are shown in Table 3. Setup 1-3, 5-6 are all with the PASM-194 at  $N_1$  AEncoder block, and BPE-3000 at the top block. We see that,  $N_1 = N_3 = 6$  with  $\beta = 0.5$  achieves relatively stable results. Furthermore, when we replacing the PASM-194 with BPE-194 for aligning the first  $N_1$  layers outputs, it obtains worse WERs than setup 2, however, when we compare it with system 2 in Table 1, we still see performance improvements. This tells us that PASM is more suitable for low-level acoustic information learning than BPE, and introducing small-to-large target units

progressive representation learning will be helpful. All these observations lead us to propose the whole structure of paCTC that shown in Fig.1(b).

#### 4.3.2. Results on Accented ASR

In Table 2, the effectiveness of PMU with its different variants are examined on the CommonVoice accented ASR task. Different from the Librispeech task, we find the best vocabulary size of both PASM and BPE baselines is 205, larger BPE size doesn’t result in better WERs under the ConformerT with single type target units. And consistent with the findings in Table 1, both the in-domain and out-of-domain performances are continuously reduced by the proposed PMU methods, such as, system 4 performs better than 5 because PASM is applied on CTC and while BPE is applied on transducer; paraCTC achieves better results than basic PMU, and paCTC significantly outperforms other two PMU variants, especially on the three in-domain test sets. It’s worth noting that, in paCTC, both the intermediate BPE-CTC and PASM-CTC are with the same 205 vocabulary size. By comparing system 7 with 8, the results also prove that introducing progressive learning with small to larger target units is useful. Finally, the paCTC with optional structure achieves the best overall WERs, compared with the best ConformerT baseline system 2, system 10 produces relative 7.7% overall WER reduction on this accented ASR testsets. Specifically, relative 8.8%, 7.6% and 10.2% WER reductions are for the in-domain England, Indian and US test sets, 8.2%, 8.6% and 7.1% WER reductions are for the out-of-domain Australia, Canada and Singapore test set, respectively.

## 5. Conclusion

In this work, we propose a phonetic-assisted multi-target units (PMU) modeling approach, to effectively leverage both the phonetic-induced PASM and conventional text-induced BPE target units modeling for improving the state-of-the-art Conformer-Transducer end-to-end ASR system. Three PMU structures are proposed with different implementation of multi-targets CTC/transducer modeling, including the basic PMU with PASM and BPE applied to CTC and transducer separately, the PMU with paraCTC where the PASM and BPE units are also integrated in a parallel way as CTC’s target units, and the PMU with paCTC that uses BPE units conditioned on the PASM CTC in a progressive representation learning manner. Results on both the LibriSpeech and accented English ASR tasks show that, the proposed PMU can significantly outperform the conventional BPE-based Conformer-Transducer E2E ASR system.

## 6. References

- [1] A. Gulati, J. Qin, C.-C. Chiu, N. Parmar, Y. Zhang, J. Yu, W. Han, S. Wang, Z. Zhang, Y. Wu *et al.*, “Conformer: Convolution-augmented transformer for speech recognition,” in *Proc. Interspeech*, 2020, pp. 5036–5040.
- [2] W. Huang, W. Hu, Y. T. Yeung, and X. Chen, “Conv-transformer transducer: Low latency, low frame rate, streamable end-to-end speech recognition,” in *Proc. Interspeech*, 2020, pp. 5001–5005.
- [3] J. Li, Y. Wu, Y. Gaur, C. Wang, R. Zhao, and S. Liu, “On the comparison of popular end-to-end models for large scale speech recognition,” in *Proc. Interspeech*, 2020, pp. 1–5.
- [4] F. Boyer, Y. Shinohara, T. Ishii, H. Inaguma, and S. Watanabe, “A study of transducer based end-to-end ASR with ESPnet: Architecture, auxiliary loss and decoding strategies,” in *IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*, 2021, pp. 16–23.
- [5] W. Zou, D. Jiang, S. Zhao, G. Yang, and X. Li, “Comparable study of modeling units for end-to-end mandarin speech recognition,” in *Proc. ICSLP*, 2018, pp. 369–373.
- [6] S. Zhou, L. Dong, S. Xu, and B. Xu, “A comparison of modeling units in sequence-to-sequence speech recognition with the transformer on mandarin chinese,” in *Neural Information Processing*, 2018, pp. 210–220.
- [7] C.-C. Chiu, T. N. Sainath, Y. Wu, R. Prabhavalkar, P. Nguyen, Z. Chen, A. Kannan, R. J. Weiss, K. Rao, E. Gonina *et al.*, “State-of-the-art speech recognition with sequence-to-sequence models,” in *Proc. ICASSP*, 2018, pp. 4774–4778.
- [8] J. Li, G. Ye, A. Das, R. Zhao, and Y. Gong, “Advancing acoustic-to-word CTC model,” in *Proc. ICASSP*, 2018, pp. 5794–5798.
- [9] A. Zeyer, K. Irie, R. Schlüter, and H. Ney, “Improved training of end-to-end attention models for speech recognition,” in *Proc. Interspeech*, 2018, pp. 7–11.
- [10] K. Rao, H. Sak, and R. Prabhavalkar, “Exploring architectures, data and units for streaming end-to-end speech recognition with RNN-transducer,” in *IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*, 2017, pp. 193–199.
- [11] R. Sennrich, B. Haddow, and A. Birch, “Neural machine translation of rare words with subword units,” in *Proc. ACL*, 2016, pp. 1715–1725.
- [12] M. Schuster and K. Nakajima, “Japanese and Korean voice search,” in *Proc. ICASSP*, 2012, pp. 5149–5152.
- [13] T. Kudo, “Subword regularization: Improving neural network translation models with multiple subword candidates,” in *Proc. ACL*, 2018, pp. 66–75.
- [14] W. Wang, G. Wang, A. Bhatnagar, Y. Zhou, C. Xiong, and R. Socher, “An investigation of phone-based subword units for end-to-end speech recognition,” in *Proc. Interspeech*, 2020, pp. 1778–1782.
- [15] M. Zeineldeen, A. Zeyer, W. Zhou, T. Ng, R. Schlüter, and H. Ney, “A systematic comparison of grapheme-based vs. phoneme-based label units for encoder-decoder-attention models,” *arXiv preprint arXiv:2005.09336*, 2020.
- [16] S. Chen, X. Hu, S. Li, and X. Xu, “An investigation of using hybrid modeling units for improving end-to-end speech recognition system,” in *Proc. ICASSP*, 2021, pp. 6743–6747.
- [17] H. Xu, S. Ding, and S. Watanabe, “Improving end-to-end speech recognition with pronunciation-assisted sub-word modeling,” in *Proc. ICASSP*, 2019, pp. 7110–7114.
- [18] Y. Higuchi, K. Karube, T. Ogawa, and T. Kobayashi, “Hierarchical conditional end-to-end ASR with CTC and multi-granular subword units,” in *Proc. ICASSP*, 2022, pp. 7797–7801.
- [19] A. Graves, “Sequence transduction with recurrent neural networks,” in *Proc. ICML*, 2012.
- [20] J.-J. Jeon and E. Kim, “Multitask learning and joint optimization for transformer-RNN-transducer speech recognition,” in *Proc. ICASSP*, 2021, pp. 6793–6797.
- [21] A. Graves, S. Fernández, F. Gomez, and J. Schmidhuber, “Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks,” in *Proc. ICML*, 2006, pp. 369–376.
- [22] R. Sanabria and F. Metze, “Hierarchical multitask learning with CTC,” in *Proc. SLT*, 2018, pp. 485–490.
- [23] J. Li, G. Ye, R. Zhao, J. Droppo, and Y. Gong, “Acoustic-to-word model without OOV,” in *IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*, 2017, pp. 111–117.
- [24] J. Kremer, L. Borgholt, and L. Maaløe, “On the inductive bias of word-character-level multi-task learning for speech recognition,” *arXiv preprint arXiv:1812.02308*, 2018.
- [25] A. Heba, T. Pellegrini, J.-P. Lorré, and R. Andre-Obrecht, “Char+CV-CTC: combining graphemes and consonant/vowel units for CTC-based ASR using multitask learning,” in *Proc. Interspeech*, 2019, pp. 1611–1615.
- [26] J. Nozaki and T. Komatsu, “Relaxing the conditional independence assumption of CTC-based ASR by conditioning on intermediate predictions,” in *Proc. Interspeech*, 2021, pp. 3735–3739.
- [27] V. Panayotov, G. Chen, D. Povey, and S. Khudanpur, “LibriSpeech: an asr corpus based on public domain audio books,” in *Proc. ICASSP*, 2015, pp. 5206–5210.
- [28] R. Ardila, M. Branson, K. Davis, M. Henretty, M. Kohler, J. Meyer, R. Morais, L. Saunders, F. M. Tyers, and G. Weber, “Common Voice: A massively-multilingual speech corpus,” in *Proc. LREC*, 2020, pp. 4218–4222.
- [29] S. Watanabe, T. Hori, S. Karita, T. Hayashi *et al.*, “ESPnet: End-to-end speech processing toolkit,” in *Proc. Interspeech*, 2018, pp. 2207–2211.
- [30] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Rethinking the inception architecture for computer vision,” in *Proc. CVPR*, 2016, pp. 2818–2826.
- [31] T. Kudo and J. Richardson, “SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing,” in *Proc. The Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, 2018, pp. 66–71.
- [32] C. Dyer, V. Chahuneau, and N. A. Smith, “A simple, fast, and effective reparameterization of IBM model 2,” in *Proc. NAACL*, 2013, pp. 644–648.