Multi-sequence Intermediate Conditioning for CTC-based ASR

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Abstract
End-to-end automatic speech recognition (ASR) directly maps input speech to a character sequence without using pronunciation lexica. However, in languages with thousands of characters, such as Japanese and Mandarin, modeling all these characters is problematic due to data scarcity. To alleviate the problem, we propose a multi-task learning model with explicit interaction between characters and syllables by utilizing Self-conditioned connectionist temporal classification (CTC) technique. While the original Self-conditioned CTC estimates character-level intermediate predictions by applying auxiliary CTC losses to a set of intermediate layers, the proposed method additionally estimates syllable-level intermediate predictions in another set of intermediate layers. The character-level and syllable-level predictions are alternately used as conditioning features to deal with mutual dependency between characters and syllables. Experimental results on Japanese and Mandarin datasets show that the proposed multi-sequence intermediate conditioning outperformed the conventional multi-task-based and Self-conditioned CTC-based methods.

Index Terms: connectionist temporal classification, multi-task learning, self-condition

1. Introduction
End-to-end automatic speech recognition (ASR) simplifies the conventional ASR pipelines by mapping input speech into a text sequence directly, without using hand-crafted pronunciation lexica. Attention-based encoder-decoders [1] and recurrent neural network transducers [2] are popular end-to-end ASR methods, in which an autoregressive decoder predicts the next token given previously estimated tokens with an encoded sequence of audio features. These autoregressive ASR methods have shown state-of-the-art performance with strong encoders such as Transformer [3] and Conformer [4]. Self-supervised learning models such as wav2vec 2.0 [5] and HuBERT [6] have shown further improvement by pretraining the encoder using a large amount of unlabeled data. On the other hand, non-autoregressive ASR methods also have a lot of attention due to their efficient inference, which can predict all tokens simultaneously. Connectionist temporal classification (CTC) [7] is a fundamental approach to non-autoregressive ASR. On top of the CTC framework, various approaches have been proposed based on iterative refinement decoding [8-10] and intermediate prediction objective [11, 12].

Although end-to-end ASR methods achieved sufficient performance in English, the challenge remains in ideogram languages such as Japanese and Mandarin that the vocabulary size is larger than that of phonogram languages [13]. For example, Japanese has over three thousand characters, and Mandarin has over four thousand characters, while English has at most about one hundred characters. Since ideographic characters in Japanese and Mandarin are rarely related to their pronuncia-

ions, many characters share the same pronunciation. Therefore, an acoustic feature should be mapped to different character labels considering language contexts. In addition, because most Japanese characters have multiple pronunciations, multiple different acoustic features should be mapped to one character label. In such a situation, end-to-end modeling of all these characters is problematic due to data scarcity.

For end-to-end modeling under the data scarcity situation, hierarchical multi-task learning with low-level auxiliary targets has been studied [14-16]. Loss functions against low-level auxiliary targets, i.e., phonemes or syllables, placed at intermediate layers can help regularize model training for the high-level targets, i.e., characters. However, there is no interaction between the low-level and high-level targets, although the low-level predictions could narrow down the candidates of the high-level predictions. In addition, if intermediate high-level predictions were given, the low-level predictions could be enhanced.

In this paper, we propose a multi-task learning-based ASR method with explicit interactions between the low-level and high-level targets. Inspired by Self-conditioned CTC [12] and HC-CTC [17], the proposed method utilizes character-level intermediate predictions as conditioning features fed into the next layers. Syllable-level predictions are additionally obtained at another set of intermediate layers to model the interaction between syllable-level and character-level predictions. The two-level conditioning layers can be placed alternately to deal with mutual dependency; not only the syllable-to-character predictions but also the character-to-syllable predictions are considered in the proposed method. Experimental results on Corpus of Spontaneous Japanese (CSI) [18] and Mandarin AISHELL-1 [19] show that the proposed multi-sequence intermediate conditioning outperformed conventional multi-task learning-based and Self-conditioned CTC-based methods.

2. Related Work

2.1. Non-autoregressive ASR
Non-autoregressive ASR approaches can be categorized into iterative refinement decoding [8,9,10] and intermediate prediction objective [11,12]. Iterative refinement decoding is comprised of an encoder and a non-autoregressive decoder, where the encoder is trained with the CTC objective, and the decoder is trained with the masked language model objective. The decoder iteratively refines an initial prediction from the encoder by editing low-confident characters with the masked language model. A drawback of the approach is that the iterative refinement processes increase the computational complexity. In contrast, our proposed method does not use a decoder while adopting intermediate prediction objectives to the CTC-based encoder. We extend the intermediate prediction objective approach by utilizing syllable-level auxiliary targets.

Index Terms: connectionist temporal classification, multi-task learning, self-condition
2.2. Multi-task ASR with low-level auxiliary targets

Multi-task learning with low-level tasks has been actively studied \cite{12,15,16}. In typical hierarchical multi-task models, low-level auxiliary tasks are placed at intermediate layers, while the main task is always placed only at the highest layer. Our proposed method differs from these methods in that the predictions for the main task are also applied in intermediate layers, and both low-level and high-level intermediate predictions are utilized for conditioning the subsequent layers.

Single-sequence one-to-one model \cite{20} can predict grapheme and phoneme sequences simultaneously by combining the multiple sequences into a single sequence. This approach is attractive because no architectural modification from typical end-to-end ASR models is required. However, it was difficult to outperform a separate grapheme-only model, possibly due to increased data scarcity.

Joint phoneme-grapheme model \cite{21} utilizes both phone and grapheme intermediate predictions with iterative refinement decoding. This model can handle mutual dependency between phoneme and grapheme sequences, while it is not directly applicable to ideogram languages for the next encoder input:

\[
X^{(n)} = \text{Encoder}^{(n)}(X^{(n-1)}) \quad (1 \leq n \leq N),
\]

where \(X^{(0)} = X\). The output sequence \(Z\) is obtained by applying a linear and the softmax functions to the encoded sequence:

\[
Z = \text{Softmax}(\text{Linear}_{D \rightarrow |V'|}(X^{(N)})),
\]

where \(\text{Linear}_{D \rightarrow |V'|}(\cdot)\) maps a \(D\)-dimensional vector into a \(|V'|\)-dimensional vector for each element in the input sequence.

3.2. Conditioning with intermediate CTC

Intermediate CTC \cite{13} introduces additional CTC predictions from intermediate encoder blocks. An intermediate prediction sequence for the \(n\)-th encoder block \(Z^{(n)} = (z_t^{(n)}) \in (0, 1)^{|V'|}|t = 1, \ldots, T\) is computed as:

\[
Z^{(n)} = \text{Softmax}(\text{Linear}_{D \rightarrow |V'|}(X^{(n)})).
\]

Note that the linear layer is shared with the output layer (Eq. 3) so that no additional parameters are added. The losses for the intermediate predictions are computed as well as the original CTC loss (Eq. 1), and the total loss is a weighted sum of the original and the intermediate CTC losses:

\[
\mathcal{L}_{\text{cte}} = (1 - \lambda)\mathcal{L}_{\text{cte}}(Z, Y) + \frac{\lambda}{|N|} \sum_{n \in N} \mathcal{L}_{\text{cte}}(Z^{(n)}, Y),
\]

where \(\lambda \in (0, 1)\) is a mixing weight and \(N\) is a set of layer indices for intermediate loss computation. Self-conditioned CTC \cite{12} further utilizes the intermediate prediction as a condition for the next encoder input:

\[
X^{(n)} = \text{Encoder}^{(n)}(X^{(n-1)}) \quad (1 \leq n \leq N),
\]

\[
X^{(n)} = \begin{cases} X^{(n)} + \text{Linear}_{|V'| \rightarrow D}(Z^{(n)}) & (n \in N), \\ X^{(n)} & (n \notin N), \end{cases}
\]

where \(\text{Linear}_{|V'| \rightarrow D}(\cdot)\) maps a \(|V'|\)-dimensional vector into a \(D\)-dimensional vector for each element in the input sequence. This linear layer is shared among the \(|N|\) intermediate layers.

4. Proposed Method: Multi-sequence Intermediate Conditioning

Figure 1 shows an overview of the proposed multi-sequence intermediate conditioning method. A syllable-level auxiliary target sequence \(Q = (q_m \in W \mid m = 1, \ldots, M)\) is prepared for each training sample, where \(W\) is a set of syllables and \(M\) is the length of the syllable sequence. Additional CTC predictions \(R^{(n)} = (r_t \in (0, 1)^{|W'|}|t = 0, \ldots, T\) for the syllable sequence are computed from intermediate layers, similar to Eq. 4:

\[
R^{(n)} = \text{Softmax}(\text{Linear}_{D \rightarrow |W'|}(X^{(n)})),
\]

where \(W' = W \cup \{\text{blank}\}\). The total loss is a weighted sum of the original CTC loss, the intermediate CTC loss against characters, and the intermediate CTC loss against syllables:

\[
\mathcal{L}_{\text{mic}} = (1 - \lambda)\mathcal{L}_{\text{cte}}(Z, Y) + \frac{\lambda}{|N| + |Q|} \sum_{n \in N} \mathcal{L}_{\text{cte}}(Z^{(n)}, Y),
\]

\[
+ \frac{\lambda}{|N| + |Q|} \sum_{n \in N} \mathcal{L}_{\text{cte}}(R^{(n)}, Q),
\]
The sets of intermediate layers $\mathcal{N}$ and $\mathcal{N}_q$ are important hyperparameters in the proposed method. In Figure 1, an example of the sets of layers for the proposed intermediate conditioning is shown: $\mathcal{N} = \{6, 12\}$ and $\mathcal{N}_q = \{3, 9, 15\}$, where character-level and syllable-level conditioning layers are alternately trained to handle the mutual dependency between the two tasks. When $\mathcal{N} \cap \mathcal{N}_q \neq \emptyset$, syllable-level and character-level conditioning are performed at the same layer by adding two embeddings from both $Z^{(n)}$ and $R^{(n)}$ to the next encoder input.

$$X_t^{(n)} = \begin{cases} 
X^{(n)} + \text{Linear}_{W^{(n)}} \cdot D(Z^{(n)}) & (n \in \mathcal{N} \setminus \mathcal{N}_q), \\
X^{(n)} + \text{Linear}_{W^{(n)}} \cdot D(R^{(n)}) & (n \in \mathcal{N}_q \setminus \mathcal{N}), \\
X^{(n)} + \text{Linear}_{W^{(n)}} \cdot D(Z^{(n)}) + \text{Linear}_{W^{(n)}} \cdot D(R^{(n)}) & (n \in \mathcal{N} \cap \mathcal{N}_q), \\
X^{(n)} & (n \notin \mathcal{N} \cup \mathcal{N}_q), 
\end{cases} \quad (10)$$

5.1. Data

Our main results were obtained using CSJ [18]. The 271-hour subset of academic presentation speech (CSJ-APS) was used for training. Since the corpus includes not only character sequences but also corresponding pronunciation labels, syllable-level sequences were extracted from the pronunciation labels as the auxiliary training targets. The character vocabulary size $|V|$ was 2753, and the syllable vocabulary size $|W|$ was 256. We used the official evaluation set: “eval1”, “eval2”, and “eval3” for testing. Although CSJ contains another 330-hour subset of simulated public speech on everyday topics (CSJ-SPS) for training, we did not use CSJ-SPS for conforming to the prior study [23]. Note that “eval1” and “eval2” were drawn from CSJ-APS, while “eval3” was drawn from CSJ-SPS, which was considered as an out-of-domain test set.

Mandarin AISHELL-1 corpus [19] was also used for evaluating the proposed method. According to the official split of AISHELL-1, the 150-hour subset was used for training. For syllable-level targets, pinyin labels without tones were automatically generated from character sequences by using pypinyin[1]. The character vocabulary size $|V|$ was 4231, and the syllable vocabulary size $|W|$ was 404.

For the input samples, 80-dimensional Mel-scale filterbank coefficients with three-dimensional pitch features were extracted using Kaldi toolkit [25]. Speed perturbation [26] and SpecAugment [27] were also applied to the training data.

5.2. Model configurations

We prepared four models with conventional methods and three variant models for our proposed method. Note that the number of parameters in these models were around 32 million for CSJ and 52 million for AISHELL-1, respectively. The number of additional parameters introduced by the proposed method was small at most 0.2 million since the additional linear layers were shared among intermediate layers.

5.2.1. Conventional models

Baseline: The Conformer-CTC model as described in Section 3.1 was used. The number of layers $N$ was 18, and the encoder dimension $D$ was 256. The convolution kernel size and the number of attention heads were 15 and 4, respectively. According to the character vocabulary size, the feed-forward layer dimension in the Conformer blocks was set differently: 1024 for CSJ, and 2048 for AISHELL-1. The model was trained for 50 epochs, and the final model was obtained by averaging model parameters over 10-best checkpoints in terms of validation loss values. The Adam optimizer [28] with $\beta_1 = 0.9$, $\beta_2 = 0.98$, the Noam learning rate scheduling [29] with 25k warmup steps, and a learning rate factor of 5.0 were used for training. CTC best path decoding [7] was used at inference, without using any language models.

Multitask: Based on the Baseline model, an additional syllable-level CTC prediction was placed at the 15-th layer, a few layers lower than the last layer, which is similar to conventional multi-task learning methods [14].

InterCTC: Five character-level intermediate CTC predictions were placed at $\mathcal{N} = \{3, 6, 9, 12, 15\}$ with $\lambda = 0.5$. Other configurations were identical to the Baseline model.

SelfCond: In addition to the InterCTC model, conditioning with the intermediate CTC predictions was applied.

[1] https://github.com/mozilla/ctc
Character-level and syllable-level predictions were placed at the same layers: $N = \{6, 12\}$ and $N_q = \{6, 12, 18\}$ with $\lambda = 0.5$.

**Hierarchical:** Character-level predictions were placed at higher layers $N = \{12, 15\}$, while syllable-level predictions were placed at lower layers $N_q = \{3, 6, 9\}$ with $\lambda = 0.5$.

**Alternate:** Character-level and syllable-level CTC predictions were placed alternately as shown in Fig. 1 $N = \{6, 12\}$ and $N_q = \{3, 9, 15\}$ with $\lambda = 0.5$.

### 5.3. Results

Table 1 shows the character error rates for CSJ and AISHELL-1 evaluation sets. The results obtained from the conventional models show that the multi-task learning model with auxiliary syllable-level predictions performed better than the baseline CTC-based model. However, a similar performance was obtained by Intermediate CTC without using the syllable-level predictions. Self-conditioned CTC was the best model among the conventional methods.

The proposed models with hierarchical and alternate conditioning strategies outperformed the conventional models on CSJ test sets. The results clearly show that the syllable-level intermediate predictions help improve the accuracy when they are used together with character-level intermediate predictions. We could not see a clear difference between the two conditioning strategies on CSJ test sets, while the alternate conditioning was slightly better than the hierarchical one for both CSJ and AISHELL-1. The results suggest that the alternate conditioning can capture mutual dependency between syllables and characters. On the other hand, parallel conditioning, i.e., character-level and syllable-level conditioning placed at the same layers, showed degradation compared with the other strategies. The results indicate that one linear layer is insufficient to simultaneously transform the shared encoder output into character-level and syllable-level predictions.

The proposed models showed significant improvement over conventional models on "eval3", which was considered as an out-of-domain test set. The results suggest that the auxiliary syllable-level prediction can improve robustness against domain mismatch, which is particularly important for large vocabulary ideogram languages with a relatively small number of training samples per character.

### Table 1: Character error rates on CSJ and AISHELL-1. The results were obtained without language models.

| Method               | Layer indices for CTC loss | Intermediate conditioning | Character eval1 | Syllable eval2 | CSJ eval3 | AISHELL-1 eval dev | AISHELL-1 eval test |
|----------------------|----------------------------|---------------------------|-----------------|---------------|-----------|-------------------|---------------------|
| **Conventional models** |                           |                           |                 |               |           |                   |                     |
| Baseline             | 18                        | N                         | 5.4             | 3.9           | 9.9       | 5.8               | 6.2                 |
| Multitask            | 18                        | N                         | 5.4             | 3.7           | 9.5       | 5.5               | 5.9                 |
| InterCTC             | 3,6,9,12,15,18            | N                         | 5.4             | 3.8           | 9.4       | 4.6               | 5.0                 |
| SelfCond             | 3,6,9,12,15,18            | Y                         | 5.3             | 3.7           | 9.2       | 4.3               | 4.6                 |
| **Proposed models**  |                           |                           |                 |               |           |                   |                     |
| Parallel             | 6,12,18                   | Y                         | 5.2             | 3.6           | 8.8       | 5.1               | 5.5                 |
| Hierarchical         | 12,15,18                  | Y                         | 5.1             | 3.6           | 8.8       | 4.3               | 4.7                 |
| Alternate            | 6,12,18                   | Y                         | 5.1             | 3.5           | 8.8       | 4.2               | 4.5                 |

### Table 2: Syllable error rates on CSJ. Results were obtained using the intermediate outputs of the 15-th layer.

| Method               | eval1 | eval2 | eval3 |
|----------------------|-------|-------|-------|
| Conventional (Multitask) | 4.0   | 2.6   | 4.8   |
| Proposed (Alternate)  | 3.8   | 2.3   | 4.3   |

### Table 3: Character error rates on CSJ compared with the prior study. CTC/Att+BeamSearch was the best autoregressive model, and Self-conditioned CTC was the best non-autoregressive model in the prior study [22].

| Method               | eval1 | eval2 | eval3 |
|----------------------|-------|-------|-------|
| CTC/Att+BeamSearch   | 5.1   | 3.5   | 8.8   |
| Self-conditioned CTC | 5.3   | 3.7   | 9.1   |
| Proposed (Alternate) | 5.1   | 3.5   | 8.8   |

### 5.4. Comparison with prior studies

Comparison results with the prior comparative study [22] for CSJ are shown in Table 3. The proposed model with alternate conditioning outperformed the best non-autoregressive ASR method: Self-conditioned CTC [22]. Moreover, the proposed model performs better than the best autoregressive ASR method with the hybrid CTC/Attention model and beam search decoding. For AISHELL-1, the recent Conformer-Transformer-based autoregressive model [29] reported 4.4%/4.7%, while the proposed method achieved 4.2%/4.5%. From the results above, it can be concluded that the proposed method achieves state-of-the-art performance by utilizing syllable-level targets.

### 6. Conclusions

We proposed an end-to-end ASR method to model the interaction between the intermediate syllable-level and character-level predictions. Experiments with two ideogram languages showed that the proposed method outperformed the conventional multi-task-based and Self-conditioned CTC-based methods.\footnote{The results in [22] were slightly better than the SelfCond model in Table 3 because the prior work used 100 epochs for training, whereas ours used 50 epochs.}
7. References

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