PHONEME BASED NEURAL TRANSDUCER FOR LARGE VOCABULARY SPEECH RECOGNITION

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ABSTRACT
To join the advantages of classical and end-to-end approaches for speech recognition, we present a simple, novel and competitive approach for phoneme-based neural transducer modeling. Different alignment label topologies are compared and word-end-based phoneme label augmentation is proposed to improve performance. Utilizing the local dependency of phonemes, we adopt a simplified neural network structure and a straightforward integration with the external word-level language model to preserve the consistency of seq-to-seq modeling. We also present a simple, stable and efficient training procedure using frame-wise cross-entropy loss. A phonetic context size of one is shown to be sufficient for the best performance. A simplified scheduled sampling approach is applied for further improvement. We also briefly compare different decoding approaches. The overall performance of our best model is comparable to state-of-the-art results for the TED-LIUM Release 2 and Switchboard corpora.

Index Terms— phoneme, neural transducer, speech recognition

1. INTRODUCTION & RELATED WORK
On reasonably sized automatic speech recognition (ASR) tasks like the TED-LIUM Release 2 (TLv2)\textsuperscript{11} and Librispeech\textsuperscript{2}, the classical hybrid hidden Markov model (HMM)\textsuperscript{3} approach still shows state-of-the-art (s.o.t.a) performance\textsuperscript{4, 5}. Its composition of individual acoustic model (AM), lexicon and language model (LM) gives strong flexibility at the cost of complexity. Additionally, as phonetic units are usually used for the AM, the hybrid HMM also shows a good scalability to low-resource tasks. However, the formulation with conditional independence assumption and approximated prior as well as the clustered acoustic modeling units\textsuperscript{6} lead to inconsistency of modeling.

Recently, the end-to-end approach, which enables the direct mapping of acoustic feature sequences to sub-word or word sequences, has shown competitive performance for ASR\textsuperscript{7, 8}. Common end-to-end models include connectionist temporal classification (CTC)\textsuperscript{9}, recurrent neural network transducer (RNN-T)\textsuperscript{10}, attention-based encoder-decoder models\textsuperscript{11, 12} and possible variants thereof. The integration of all components into one powerful neural network (NN) for joint optimization leads to a great simplicity at the cost of less flexibility. Additionally, the straightforward seq-to-seq modeling results in more consistent training and inference. However, good performance usually requires large amount of training data and/or data augmentation\textsuperscript{8} as well as much longer training.

Attempts to join the advantages of both approaches have been arising. In\textsuperscript{13}, phoneme-based sub-word units are applied to attention models. Together with an external lexicon and both sub-word and word-level LMs, the overall system achieved s.o.t.a results on the Switchboard task. More relevant to this work is the hybrid autoregressive transducer (HAT)\textsuperscript{14}, which can be regarded as one variant of RNN-T. Using phonemes as label units, HAT formulates the problem into a generative modeling by exploring the internal prior of the model and obtained large improvement over the baseline RNN-T. Additionally, limited phonetic context (above 2) is shown to retain the performance of full context modeling, which is also verified by sub-word-based RNN-T\textsuperscript{15}.

Following this motivation, we investigate phoneme-based neural transducer models in this work. We compare different alignment label topologies for transducer modeling and propose phoneme label augmentation to improve performance. Similar as LM shallow fusion\textsuperscript{16}, we apply a straightforward integration with the external word-level LM to maximally keep the consistency of modeling. Unlike HAT, we avoid the effect of models’ internal prior by utilizing the local context dependency of phonemes (co-articulation), which leads to a simplified NN structure without separate blank distribution. Similar as in\textsuperscript{17}, we explore a simplified, stable and efficient training procedure using frame-wise cross-entropy (CE) loss and apply a simplified scheduled sampling\textsuperscript{18} approach to further improve performance. The necessity of larger phonetic context size (above 1) and different decoding approaches are also investigated. Experiments on the TLv2 and 300h-Switchboard (SWBD)\textsuperscript{19} corpora show that our best results are comparable with s.o.t.a performance.

2. PHONEME-BASED NEURAL TRANSDUCER
2.1. Model definition & label topology
Let $x_1^T$ and $a_1^T$ denote the input feature sequence and output phoneme label sequence, respectively. And let $h_1^T =\ldots$
Theoretically, we can also introduce \( k \) with an additional transition sequence \( s_{-1}^k \), where \( y_u \) is mapped to \( a_s^u \). Note that \( s_u \in \{ s_{u-1}, s_{u-1} + 1 \} \) and \( 0 \leq s_u \leq S \) at each alignment step \( u \), where \( s_u = 0 \) stands for no label yet. This also allows label repetition in \( a_s^u \).

The output label sequence posterior can be obtained as:

\[
p(a_s^u | x_1^T) = \sum_{(y,s)\in\mathcal{A}_T^u} p(y_u | a_s^{u-1}, h_1^T)
\]

Here we compare two different alignment label topologies for neural transducer modeling, which further defines Eq. (1) into two different probabilistic modeling approaches.

### 2.1.1. RNA topology

The first topology is the same as recurrent neural aligner (RNA) \([20]\) or monotonic RNN-T \([21]\), where each \( a_s \) appears only once in \( y_1^u \) and the rest of \( y_1^u \) is filled with the additional blank label \( \langle \rangle \). Following \([17]\), we call this the RNA topology. In this case, \( y_1^u \) can fully define \( s_1^u \), as \( y_{u} = \langle \rangle \) represents \( s_u = s_{u-1} \) and \( y_{u} \neq \langle \rangle \) represents \( s_u = s_{u-1} + 1 \). Thus, Eq. (1) can be directly simplified as:

\[
p(a_1^S | x_1^T) = \sum_{(y,s)\in\mathcal{A}_T^u} p(y_u | y_1^{u-1}, h_1^T) = \sum_{(y,s)\in\mathcal{A}_T^u} p(y_u | a_s^{u-1}, h_1^T)
\]

where \( p(y) \) is the underlying parameterized decoder, which estimates a probability distribution over the full label vocabulary including \( \langle \rangle \) based on the given label context and encoder output. Here we additionally introduce \( k \) to define the context size. With \( k = s_{u-1} \), Eq. (2) leads to the standard definition of RNN-T with full context and strict monotonicity. Theoretically, we can also introduce \( u_s \) to denote positions in \( y_1^u \) where \( a_s \) occurs and reformulate Eq. (2) into a segmental modeling, which however, is not investigated in this work.

### 2.1.2. HMM topology

The second one is the classical HMM topology which is widely used for alignment in the hybrid HMM approach. Instead of using \( \langle \rangle \), each \( a_s \) can loop for multiple steps in \( y_1^u \), where additional non-speech labels, e.g., silence, may also be introduced for \( a_s \). We can then define Eq. (1) as:

\[
\sum_{(y,s)\in\mathcal{A}_T^u} \prod_{u=1}^{U} p(s_u | y_1^{u-1}, s_1^{u-1}, h_1^T) \cdot p(x_1^T | s_1^{u-1}, s_1^{u-1}, h_1^T)
\]

where \( p(s_u | y_1^{u-1}, s_1^{u-1}, h_1^T) \) is defined as:

\[
\begin{align*}
\delta_{y_u, y_{u-1}, \langle \rangle} a_{s_{u-1}-k}^u h_1^T, & \quad s_u = s_{u-1} \\
1 - \delta_{y_u, y_{u-1}, \langle \rangle} a_{s_{u-1}-k}^u h_1^T, & \quad s_u = s_{u-1} + 1
\end{align*}
\]

and \( p(y_u | y_1^{u-1}, s_1^{u-1}, h_1^T) \) is defined as:

\[
\begin{align*}
\delta(y_u | y_{u-1}, s_{u-1}^{u-1+k} h_1^T), & \quad s_u = s_{u-1} - 1 \\
\phi(y_u | a_s^{u-1} h_1^T), & \quad s_u = s_{u-1} - 1 + 1
\end{align*}
\]

Similarly, \( q_{\theta} \) is the underlying parameterized decoder. Note that at forward transitions, this definition first computes a non-loop probability as in Eq. (2) using the previous context, which is necessary for proper normalization, and then computes the next label probability with the updated context.

### 2.2. Decision and decoding

Together with an external word-level LM and lexicon, the final best word sequence can be decided as:

\[
x_1^T \rightarrow \tilde{w}_1^N = \arg \max_{w_1^N} p^\lambda(w_1^N) \sum_{a_1^T \in \mathcal{A}_T^u} p(a_1^S | x_1^T)
\]

\[
= \arg \max_{w_1^N} p^\lambda(w_1^N) \sum_{(y,s)\in\mathcal{A}_T^u} p(y_u | a_s^{u-1}, h_1^T)
\]

\[
= \arg \max_{w_1^N} p^\lambda(w_1^N) \max_{(y,s)\in\mathcal{A}_T^u} p(y_u | a_s^{u-1}, h_1^T)
\]

where \( \lambda \) is the LM scale. Similar as for phoneme-based attention model \([22]\), this decision rule simply adopts a log-linear model combination to maximally keep the consistency of seq-to-seq modeling, which we extend into the framework of phoneme-based transducer model. Eq. (3) and Eq. (5) correspond to full-sum and Viterbi decoding, respectively.

We apply lexical prefix tree search with score-based pruning and optional LM look-ahead \([23]\). For the best trade-off between simplicity and performance, we set \( k = 1 \) for our phoneme transducer models. This allows us to compute the scores of all possible label context at each step \( u \) in a single batch forwarding, which are then cached for efficient reuse in decoding. Hypotheses are recombined, either summation or maximization, based on model and decoding settings.

### 2.3. Label augmentation

Word boundary information has been adopted to improve ASR performance for both hybrid HMM approach \([24, 25]\) and phoneme-based end-to-end approach \([22, 26]\). The latter inserted a separate end-of-word (EOW) label to the phoneme inventory, which however, does not correspond to any acoustic realization. We propose to augment the phoneme inventory with EOW discrimination by identifying each phoneme appearing at word end to be a different class than that appearing within the word. This label augmentation effectively increases the size of the label vocabulary by a factor of two, which is still very small and simple for phonemes. Besides, we also investigate the effect of applying the same for start-of-word (SOW) in addition to EOW. This increases the vocabulary size by a factor of four due to phonemes appearing at both SOW and EOW, i.e., single-phoneme pronunciation.

### 2.4. Simplified NN architecture & training

We use a simplified NN architecture derived from the RNN-T network structure \([10]\). The encoder contains 6 bidirectional long short-term memory (BLSTM) layers with 512 units for each direction. We apply sub-sampling by a factor of 2 via max-pooling after the third stack of BLSTM layers. A small context size \( k \) leads to a feed-forward neural network
(FFNN)-based instead of recurrent neural network (RNN)-based decoder. We use label embedding of size 128 and 2 linear layers of size 1024 and tanh activation. The encoder and FFNN outputs are simply summed up and fed to a final softmax layer to predict the posterior distribution over the full label vocabulary. This simplified NN structure is used throughout this work for both label topologies.

Standard training of transducer models requires full-sum over all possible alignments on the whole sequence, which can be both time and memory consuming. Similar as in [17], we apply Viterbi approximation to train our transducer model using frame-wise CE loss w.r.t. $p(y_i^T, s_i^T \mid h_i^T)$ and a fixed external alignment. For the HMM topology, this also includes the non-loop probability in Eq. (3) at forward transitions. For the alignment generation, as a simple pre-stage of training, we mainly consider hybrid HMM and CTC models, both of which are easy and fast to obtain. Such simplification also allows us to apply additional techniques to further speed up training and improve performance (Section 3).

3. EXPERIMENTS

3.1. Setup

Experimental evaluation is done on the TLv2 [1] and SWBD [19] corpora with the official lexicons (TLv2: 39 phonemes and 152k words; SWBD: 45 phonemes and 30k words). An additional silence label is used for the HMM topology, while a blank label for the RNA topology. For SWBD, the Hub5’00 and Hub5’01 datasets are used as dev and test set, respectively. All the LMs used are the same as in [3] for TLv2 and [28] (sentence-wise) for SWBD. By default, word error rate (WER) results are obtained with full-sum decoding and a 4-gram LM.

We extract gammatone features from 25ms windows with 10ms shift (TLv2: 50-dim; SWBD: 40-dim). By default, we use the hybrid HMM alignment and treat the last frame of each phoneme segment as $u_s$ for the RNA topology. To speed up training, sequences are decomposed into chunks (TLv2: 256 frames; SWBD: 128 frames) with 50% overlap and a mini-batch of 128 chunks is used. An all-0 embedding is used for the initial computation. SpecAugment [8] is applied as done in [3]. We firstly pretrain the encoder with frame-wise CE loss [29] for about 5 full epochs and then keep this encoder loss in further training with a focal loss factor 1.0 [30]. We use the Nadam optimizer [31] with initial learning rate (LR) 0.001, which is kept constant for about 6 full epochs in total. Additionally for the output CE loss of the RNA topology, we apply 0.2 label smoothing [33], and boost the loss at positions $u_s$ by a factor of 5 to balance the large number of blank frames in the alignment.

3.2. Label unit & topology

We firstly compare the RNA topology and the HMM topology for neural transducer modeling. For both topologies, we evaluate the original, EOW-augmented and SOW+EOW-augmented phoneme label units (Section 2.3). Our label augmentation is applied only to speech phonemes. Table 1 shows the WER results for both TLv2 and SWBD. For all three types of labels, the RNA topology shows consistently much better performance than the HMM topology, which appears to be more suitable for transducer modeling. In all cases, the EOW-augmented phoneme labels clearly improve over the original phoneme labels. Applying SOW in addition to EOW brings no further improvement but small degradation. This is intuitively clear as the SOW information is redundant for the model given the predecessor label with EOW information. Also the additional separation of single phoneme pronunciations might result in data sparsity problem. We use the EOW-augmented phoneme labels and the RNA topology for all further investigations.

3.3. Alignment

For CE training using the hybrid HMM alignment, we can theoretically select any frame within each phoneme segment to be $u_s$ and treat the rest including silence to be ($b$). Here we compare three different within-segment positions for $u_s$, namely, the first frame (segBeg), the middle frame (segMid) and the last frame (segEnd). Additionally, we also evaluate the alignment generated by phoneme-based CTC models. In this case, the alignment is really peaky as more than 95% of the phoneme labels only consume one or two frames. And more than 30% of them do not overlap with the corresponding segment in the hybrid HMM alignment. We simply choose segEnd for $u_s$. The WER results are shown in Table 2. For both corpora, our default setup performs the best. The difference among different cases is also not large, which can be further closed by more careful tuning. This suggests that our training procedure is rather stable w.r.t. different alignments of different properties.

3.4. Context

We also investigate the necessity of larger phoneme context size by varying $k \in \{1, 2, \infty\}$. For $k = \infty$, we replace the linear layers in the decoder with LSTM layers and no chunking is applied in training. The results are shown in Table 3. For CE loss with chunk-wise training, increased context size is not helpful, possibly due to the context loss at beginning of each chunk. Without chunking, increasing $k$ from 1 to 2 is
Table 3: WER of different context and training; and training time in min/epoch [m/ep] on a single GTX 1080 Ti GPU.

| Loss | Chunk | k | TLv2-dev | Hub5’00 |
|------|-------|---|----------|---------|
| CE   | yes   | 1 | 6.9      | 93.134  |
|      |       | 2 | 7.0      | 13.6    |
|      | no    | 1 | 7.2      | 14.1    |
|      |       | 2 | 7.0      | 13.8    |
| FS   |       | ∞ | 9.0      | 250.372 |

Table 4: WER of ablation study and sampling.

| Training | TLv2 | Hub5’00 |
|----------|------|---------|
| default  | 6.9  | 13.4    |
| SpecAugment | 8.5  | 14.6    |
| chunking | 7.2  | 14.1    |
| encoder loss | 7.3  | 14.0    |
| label smooth | 8.0  | 14.2    |
| lossBoost_u | 9.9  | 16.4    |
| + sampling | 6.9  | 12.9    |

Table 5: WER of different decoding.

| Decoding | TLv2-dev | Hub5’00 |
|----------|----------|---------|
| Viterbi  | 7.1      | 13.0    |
| full-sum | 6.9      | 12.9    |

Table 6: Overall WER on TLv2 and results from literature.

| Work | Modeling | Label | LM | Hub5’00 |
|------|----------|-------|----|---------|
| [17] | Attention | sub-word | RNN | 9.3 |
| [17] | hybrid HMM | triphone | LSTM | 5.6 |
| this | Transducer | phoneme | LSTM | 5.9 |
|      |          |        | Trafo | 5.4 |

Table 7: Overall WER on SWBD and results from literature.

| Work | Modeling | Label | LM | Hub5’00 |
|------|----------|-------|----|---------|
| [36] | Attention | sub-word | none | 13.5 |
| [36] | hybrid HMM | phoneme-state | LSTM | 11.7 |
| [4]  | Trafo |       | RNN | 10.5 |
|      |          |        | Trafo | 9.8 |
| this | Transducer | phoneme | LSTM | 11.5 |
|      |          |        | Trafo | 11.2 |

For our best model, we apply one-pass recognition with an LSTM LM to generate lattices that are further used for rescoring using a Transformer (Trafo) [35] LM. The results are shown in Table 6 for TLv2 and Table 7 for SWBD. We also include other results from the literature, which compare different modeling approaches using different labels. For TLv2, our best result is very close to the s.o.t.a performance [4], which applied additional speaker adaptive training and sequence discriminative training. For SWBD, our best result is comparable but still behind the s.o.t.a. performance [7], which, however, used much more epochs for training.

4. CONCLUSION

In this work, we presented a simple, novel and competitive approach for phoneme-based neural transducer modeling, which preserves advantages of classical and end-to-end systems. By utilizing a limited context dependency of phonemes, we adopt a simplified NN structure and a straightforward integration with the external word-level LM to maintain the consistency of modeling. We also described a detailed training pipeline allowing a simple, stable and efficient training of transducer models using frame-wise CE loss. The RNA label topology is shown to be more suitable for transducer modeling than the HMM topology. The proposed EOW-augmented phoneme labels bring consistent improvement over the original phoneme set. A phonetic context size of one is shown to be sufficient for the best performance with chunk-wise training. The simplified sampling approach brings further improvement on the converged model for SWBD. We also briefly compared different decoding approaches. The overall performance of our best model is on par with s.o.t.a results for TLv2 and comparable to s.o.t.a performance for SWBD.

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