Towards a Competitive End-to-End Speech Recognition for CHiME-6 Dinner Party Transcription

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Abstract

While end-to-end ASR systems have proven competitive with the conventional hybrid approach, they are prone to accuracy degradation when it comes to noisy and low-resource conditions. In this paper, we argue that, even in such difficult cases, some end-to-end approaches show performance close to the hybrid baseline. To demonstrate this, we use the CHiME-6 Challenge data as an example of challenging environments and noisy conditions of everyday speech. We experimentally compare and analyze CTC-Attention versus RNN-Transducer approaches along with RNN versus Transformer architectures. We also provide a comparison of acoustic features and speech enhancements. Besides, we evaluate the effectiveness of neural network language models for hypothesis re-scoring in low-resource conditions. Our best end-to-end model based on RNN-Transducer, together with improved beam search, reaches quality by only 3.8% WER abs. worse than the LF-MM-TDN-F CHiME-6 baseline. With the Guided Source Separation based training data augmentation, this approach outperforms the hybrid baseline by 2.7% WER abs. and the end-to-end system best known before by 25.7% WER abs.

Index Terms: End-to-end speech recognition, CHiME-6 Challenge, RNN-Transducer.

1. Introduction

In last years, active development of deep learning techniques has allowed researchers to make a great improvement of Automatic Speech Recognition (ASR) systems performance. Although conventional hybrid ASR systems have been remaining preferred for a long time, their ever-increasing difficulty of construction and training has led to an interest in end-to-end approaches. Unlike HMM-DNN-based, these methods are trained to directly map input acoustic feature sequence to sequence of characters with a single objective function that is highly relevant to the final evaluation criteria (e.g., WER). The freedom from the necessity of intermediate modeling, such as acoustic and language models with pronunciation lexicons, makes the process of building the system clearer and more straightforward.

Also, there is an informal competition in accuracy between these systems. In most speech recognition tasks with good sound conditions and speech quality (e.g. LibriSpeech), end-to-end models’ performance is great. However, in case of robust far-field speech recognition in noisy environments and with low resources, such models face problems.

There is a series of CHiME Challenges, which task is to encourage researchers to solve the problem of speech recognition in such conditions. According to the previous CHiME-5 Challenge reports, the leading positions in quality can be reached only by conventional hybrid systems. Attempts to get a somehow comparable result for end-to-end systems have not shown any notable success.

There is a new line of research, getting interesting to some scientists recently, aimed at solving a similar problem of multi-channel robust speech recognition task using the end-to-end approaches. Works such as demonstrate the effectiveness of joint training of neural network based front-end (speech enhancement) and back-end (speech recognition) models compared to the use of separate models. However, in case of utterance boundaries are given, currently the most effective approach is the speech enhancement technique based on spatial GMM blind source separation, named Guided Source Separation (GSS). Thus, while maintaining the flexibility of end-to-end modeling, combining the same GSS front-end and end-to-end models might be capable of achieving the quality of classic hybrid systems for a difficult CHiME-6 dinner party recognition task.

This paper describes an investigation of the aforementioned conjunction of techniques. We use the sixth CHiME Challenge data, as it has an additional accurate array synchronization, and the baselines for speech enhancement and recognition. Our experimental setup is focused on the replacement of hybrid recognition system from the baseline with an end-to-end system. We explored the effectiveness of RNN and Transformer architectures along with CTC-Attention and RNN-Transducer training-decoding approaches.

This study also considers some extensions for the classic RNN-T model:

- Transformer-transducer. The idea behind this approach is to replace conventional LSTM/BLSTM encoder and predictor modules of the classic RNN-T implementation with the Transformer networks, which have proven effective in sequence modeling tasks.
- Improved beam search for RNN-T decoding. It is a modification of the standard beam search algorithm aimed at improving the computational decoding efficiency by using hypothesis pruning heuristics.
- AWD-LSTM-LM for hypotheses re-scoring. This approach is to apply various regularisation strategies to aid an overfitting caused by low text data amount.

*Equal contribution.

https://chimechallenge.github.io/chime6/
• The use of GSS-based speech enhancement for training and testing data [23, 24].

The rest of the paper is organized as follows. Section 2 provides a review of common end-to-end ASR approaches. The CHiME-6 data and baseline are described in Section 3. Section 4 provides an experimental setup for the data and strategies along with a discussion of our findings. Finally, Section 5 presents our conclusions and future work.

2. End-to-end ASR overview

2.1. CTC-Attention

Connectionist temporal classification (CTC), originally introduced in [3], in the ASR field is implied as a type of neural network output and associated scoring function for training sequence-to-sequence (Seq2Seq) models. This approach is intended to relax the requirement of one-to-one mapping (alignment) between the input and output sequences. It uses an intermediate label representation with a special “blank” symbol indicating that no label is seen. It is also used when the label is repeated. One of the key features worth mentioning is the conditional independence of labels at inference, which hinders the effective usage of CTC models without an external language model.

The attention-based encoder-decoder approach, in contrast to CTC, incorporates contextual information by using both the input frames and the history of the target label for the inference process [25]. It learns to predict the alignment between frames and labels using the attention mechanism. While generally performing better than CTC, attention-based approaches are more susceptible to the noise and require more efforts to train. It is proven effective to combine these approaches to alleviate their shortcomings and improve the recognition quality [26].

Typical CTC-Attention architecture contains deep RNN (mostly, bi- or unidirectional LSTM) encoder and unidirectional RNN decoder with optional use of an external language model (LM).

2.2. Transformer

Examining ASR Seq2Seq models, it is worth mentioning Transformer architecture. Originally proposed for neural machine translation (NMT) [27], it delivers generally better accuracy compared to RNN [28]. The Transformer incorporates self-attention to utilize sequential information in contrast to the recurrent connection employed in RNN. Similar to traditional CTC-Attention, it uses joint CTC- and attention-based decoding.

Transformer architecture consists of both deep Multi-head attention (MHA) encoder and decoder. To represent the time location, linear or convolutional positional encoding is applied before encoder and decoder modules.

2.3. Neural Transducer

The main alternative to CTC-Attention is the neural transducer [29]. In many details, this approach is similar to CTC. They both use the “blank” label and compute the probability of all possible alignment paths during training to obtain the probability of the whole target transcription. Architecturally, while having essentially the same encoder, the decoder of the neural transducer differs from the attention-based. It consists of:

• Prediction network, which plays the role of a language model.
• Joint network, which tries to align audio and label sequences.

The standard neural transducer structure is presented in Figure 1. An input acoustic feature sequence \( x = (x_0, x_1, x_2, ..., x_t) \) goes to the Encoder and converts to a sequence of embeddings \( h = (h_0, h_1, h_2, ..., h_T) \). In most cases, the Encoder performs subsampling due to convolutional layers, therefore \( T' \leq T \). Next, the Joiner, which is a shallow fully connected (FC) neural network, receives the current Encoder embedding \( h_t \) and predictor embedding \( g_u \) to yield logits \( z_{t,u} \). The most probable label \( y_u \) is determined by the Softmax. It is important that, since the Predictor practically works like a neural LM, it accepts only a non-blank \( y_{u-1} \). For the blank \( y_{u-1} \), it yields \( g_u \) as if for the last non-blank \( y_{u-1} \).

Traditionally, most neural transducer studies investigate the RNN-transducer (RNN-T). It consists of deep bi- or unidirectional LSTM encoder and unidirectional LSTM predictor. Originally introduced in [20], the neural transducer is claimed to be able to reach better accuracy with the use of the Transformer as the architecture of encoder or predictor. Their transformer-transducer outperforms the classic RNN-T model for the Librispeech task.

Apart from architecture improvement, the neural transducer beam search is also can be improved. Work [21] introduces expand beam and state beam parameters to explicitly limit the size of the beam in the decoding process, and thus, increase decoding efficiency. These parameters allow to reject “bad” hypotheses and to choose only the most probable, in terms of confidence, in the predictions of the neural network.

3. CHiME-6 dinner party transcription

The previous CHiME-5 Challenge provided fully transcribed speech materials collected with multiple 4-channel microphone arrays from real dinner parties that have taken place in real homes. Conversational speech with a large amount of overlapped segments recorded in reverberant and noisy conditions...
significant complications recognition. Details on the Challenge can be found in [13].

CHiME-6 Challenge [30] uses the same recordings as the previous one, but improves initial data preparation and establishes the following strong baselines:

- Two stages array synchronization by frame-dropping and clock-drift. This allows to obtain utterances with the same start and end time on every device.
- GSS-based speech enhancement [19] applied to multiple arrays.
- Factorized time-delayed neural network (TDNN-F) acoustic model, trained with lattice-free maximum mutual information (LF-MMI), from Kaldi toolkit.

This baseline demonstrates 51.76% WER on the development set by using train_worn_simu_u400k_cleaned_rvb training set.

4. Experimental Setup

We used the ESPnet speech recognition toolkit [31] as the main framework for the experiments. It supports most of the basic end-to-end models and training pipelines.

4.1. End-to-end modeling

The first task was to discover the most suitable end-to-end architecture for this task. Approaches like joint CTC-Attention, RNN-Transducer, and Transformer are the most popular for ASR tasks. The quasi-optimal configurations of end-to-end architectures for our task are presented in Table 1. "T-T" and "dp" stand for Transformer-Transducer and dropout, respectively. The Transformer network acts as the Encoder in this architecture.

Table 1: Models configuration

|                | Encoder     | Attention     | Decoder    |
|----------------|-------------|---------------|------------|
| CTC-Attention  | VGG-BLSTM, 6-layer 512-units, dp 0.4 | 1-head 256-units, dp 0.4 | LSTM, 2-layer 256 units, dp 0.4 |
| RNN-T          | VGG-BLSTM, 6-layer 512-units, dp 0.4 | LSTM, 2-layer 256 units, dp 0.4 | FC 256 units |
| T-T            | MHA, 12-layer 1024-units, dp 0.4 | 8-head 512-units, dp 0.4 | LSTM, 2-layer 256 units, dp 0.4 |
| Transformer    | MHA, 12-layer 1024-units, dp 0.5 | 4-head 256-units, dp 0.5 | MHA, 2-layer 1024-units, dp 0.5 |

For all the approaches presented, we used a convolutional network (CNN) in front of the encoder. It consists of four Visual Geometry Group (VGG) CNN layers designed to compress the input frames in time scale by the factor of 4. Thus, after applying this network, the output features represent the transformed information from 4 primal frames. Although not originally intended, this approach allows the model to converge more stably.

4.2. Experimental evaluation

We used the official data from the Kaldi baseline recipe: train_worn_simu_u400k_cleaned_rvb and dev_gss_multiarray (or dev_gss12) in our simplified notation) as the training and development sets, respectively. There were only 40 hours of unique training data. After various types of augmentation, specifically room simulation, speed and volume perturbation, the total amount of data became about 1400 hours.

Characters (26 letters of the English alphabet and 7 auxiliary symbols) were used as acoustic units. Other versions of word units, namely position-depending letters, Byte Pair Encoding (BPE) [32] with different numbers of units 500, 1000, 2000 led only to performance degradation. This might be due to the lack of training data for such large unit numbers.

The next step was choosing input acoustic features. The hybrid baseline model used 40-dimensional high-resolution MFCC vectors (hires) concatenated with 100-dimensional i-vectors. However, such features may not be the best option for an end-to-end model. For the baseline data, we extracted the following features: 80-dimensional log-Mel filterbank coefficients (fbank), 3-dimensional pitch features, 512-dimensional wav2vec features [33]. Comparison of acoustic features with the RNN-T model with sub-optimal parameters (Table 1) is shown in Table 2. All decoding results were obtained using the beam size of 10.

Table 2: RNN-T features comparison

| Features     | Dimension | WER(%) |
|--------------|-----------|--------|
| wav2vec      | 512       | 68.3   |
| hires+i-vectors (baseline) | 40+100 | 64.1   |
| hires        | 40        | 63.6   |
| fbank        | 80        | 60.4   |
| fbank+pitch  | 80+3      | 59.7   |

Limited computing power did not allow us to train the wav2vec features extractor for a sufficient number of epochs (the model was trained only in 6 epochs), which apparently caused such a bad result. The underperforming of hires+i-vectors against the single hires might be due to the VGG network usage. All further experiments were carried out using fbank+pitch features.

Having settled on 33 character acoustic units and fbank+pitch acoustic features, we compared end-to-end architectures from the Table 1. We also used SpecAugment [34] for additional training data augmentation. The results of this comparison are presented in Table 3.

The results show that the RNN-T performs the best in this task. It is worth noting the great positive impact of SpecAugment. The applying of this augmentation reduced WER by 4.2% for the RNN-T model. This suggests the importance of
augmentation methods for low-resource tasks. Models that utilize the Transformer architecture (T-T, Transformer) perform worse than LSTM due to severe overfitting.

We also faced a problem in the rescoring process using external RNN-based language models. Character and word-based LSTM LMs (1-layer 1024-units) were trained on the training data transcriptions. However, the use of these LMs for hypothesis rescoring in the beam search algorithm for RNN-T only led to a decrease in recognition accuracy. We also used a pretrained AWD-LSTM-LM, which has shown significant WER improvement during lattice rescoring in the STC CHiME-6 system [24]. Unfortunately, none of these models improved accuracy. We have two ideas about this. The first one is that in case of a low-resource task, a regular RNN-T with well-chosen parameters of the Predictor network is able to show sufficiently good results without any rescoring techniques. The second one is that the beam search algorithm we used is not optimal for the hypothesis rescoring. For example, in the case of a hybrid system, there are separate acoustic and language model scores of a word unit. And in the rescoring algorithm, the language score is re-weighted according to the external LSTM LM. But in the case of RNN-T, there is only one single score for word unit. The default ESPnet rescoring just adds the weighted score of external LSTM LM to RNN-T weight. The results of hypothesis rescoring with an external NNLM are showed in Table 4. We used the beam size of 10 and NNLM weight of 0.3 for all experiments.

The improved beam search algorithm, implemented concerning [21], demonstrated results beyond expectations. Values expand_beam and state_beam handpicked as 2 and 1 respectively allow us to accelerate the decoding process by an average of 15-20 % with a simultaneous improvement in the recognition quality by 0.5 WER, delivering 55.00 WER for the dev_gss12. We assume that the WER improvement is due to a decrease in the impact of the Predictor overfitting.

We also applied additional GSS-based speech enhancement for the training (train_gss) data according to [24] as well as improved 24-microphone GSS enhancement for the development data (dev_gss24).

For the CHiME-6 development data, the final comparison of the currently published end-to-end models, the official baseline, and our RNN-T models is presented in Table 5. Note that results from [15] and [16] are obtained for the CHIME-5 data, i.e. without improvements mentioned in Section 3. For the sake of fair comparison between end-to-end and hybrid systems, we also report the best single model from the STC CHiME-6 system [24], as it is the best hybrid system known to us at the moment.

| Model | WER(%) |
|-------|--------|
| Joint CTC/Attention E2E | 82.1 |
| CNN-based Multichannel E2E | 80.7 |
| CHiME-6 TDNN-F baseline | 51.7 |
| RNN-T + dev_gss12 | 55.0 |
| RNN-T + train_gss + dev_gss12 | 52.6 |
| RNN-T + train_gss + dev_gss24 | 49.0 |
| Hybrid system (n-gram LM) | 36.8 |
| Hybrid system (AWD-LSTM-LM) | 33.8 |

5. Conclusion

In this work, we presented an end-to-end systems exploration of the robust far-field speech recognition in noisy environments and low resources such as the CHiME-6 task. We have shown that combining powerful GSS-based speech enhancement and end-to-end model training approach is able to achieve competitive results with hybrid systems. By using the improved beam search algorithm and addition speech enhancement, our system outperforms the hybrid baseline system by 2.7% WER abs.

Further research might be the study of the improvement absence of recognition accuracy that has arisen with the hypotheses rescoring using external NNLM. Also, it is interesting to incorporate GSS-based enhancement in the end-to-end pipeline to train the system jointly.

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