A REVIEW OF ON-DEVICE FULLY NEURAL END-TO-END AUTOMATIC SPEECH RECOGNITION ALGORITHMS

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ABSTRACT
In this paper, we review various end-to-end automatic speech recognition algorithms and their optimization techniques for on-device applications. Conventional speech recognition systems comprise a large number of discrete components such as an acoustic model, a language model, a pronunciation model, a text-normalizer, an inverse-text normalizer, a decoder based on a Weighted Finite State Transducer (WFST), and so on. To obtain sufficiently high speech recognition accuracy with such conventional speech recognition systems, a very large language model (up to 100 GB) is usually needed. Hence, the corresponding WFST size becomes enormous, which prohibits their on-device implementation. Recently, fully neural network end-to-end speech recognition algorithms have been proposed. Examples include speech recognition systems based on Connectionist Temporal Classification (CTC), Recurrent Neural Network Transducer (RNN-T), Attention-based Encoder-Decoder models (AED), Monotonic Chunk-wise Attention (MoChA), transformer-based speech recognition systems, and so on. These fully neural network-based systems require much smaller memory footprints compared to conventional algorithms, therefore their on-device implementation has become feasible. In this paper, we review such end-to-end speech recognition models. We extensively discuss their structures, performance, and advantages compared to conventional algorithms.

Index Terms— end-to-end speech recognition, attention-based model, recurrent neural network transducer, on-device speech recognition

1. INTRODUCTION
The advent of deep learning techniques has dramatically improved the accuracy of speech recognition models [1]. Deep learning techniques first saw success by replacing the Gaussian Mixture Model (GMM) of the Acoustic Model (AM) part of the conventional speech recognition systems [2] with the Feed-Forward Deep Neural Networks (FF-DNNs), further with Recurrent Neural Network (RNN) such as the Long Short-Term Memory (LSTM) networks [3] or Convolutional Neural Networks (CNNs). In addition to this, there have been improvements in noise robustness by using models motivated by auditory processing [4] [5] [6], data augmentation techniques [7] [8] [9], and beam-forming [10]. Thanks to these advances, voice assistant devices such as Google Home [11] and Amazon Alexa have been widely used at home environments.

Nevertheless, it was not easy to run such high-performance speech recognition systems on devices largely because of the size of the Weighted Finite State Transducer (WFST) handling the lexicon and the language model. Fortunately, all-neural end-to-end (E2E) speech recognition systems were introduced which do not need a large WFST or an n-gram Language Model (LM) [12]. These complete end-to-end systems have started surpassing the performance of the conventional WFST-based decoders with a very large training dataset [13] and a better choice of target unit such as Byte Pair Encoded (BPE) subword units.

In this paper, we provide a comprehensive review of the various components and algorithms of an end-to-end speech recognition system. In Sec. 2, we give a brief overview of the various neural building blocks of an E2E Automatic Speech Recognition (ASR) model. The most popular E2E ASR architectures are reviewed in Sec. 3. Additional techniques used to improve the performance of E2E ASR models are discussed in Sec. 4. Techniques used for compression and quantization of the all-neural E2E ASR models are covered in Sec. 5. Sec. 6 gives a summary of the paper.

2. NEURAL NETWORK COMPONENTS FOR END-TO-END SPEECH RECOGNITION

Table 1: Size of the intermediate buffer required for streaming speech recognition [15]. $L$ is the sequence length, $D$ is the unit size or the dimension of each layer, and $T$ is the filter width of convolution. Refer to Sec. 2 about how to obtain the typical values shown in this table.

| Model              | Memory Footprint | Typical Value | Intra-Sequence Parallelism |
|--------------------|------------------|---------------|----------------------------|
| LSTM               | $O(LD)$          | 9KB           | X                          |
| Convolution        | $O(TLD)$         | 245KB         | O                          |
| Self-attention     | $O(LND)$         | 12MB          | O                          |

Fig. 1 illustrates neural network components commonly employed in end-to-end speech recognition systems. Gated RNNs such as LSTMs and Gated Recurrent Units (GRUs) [16] have been used from the early days of encoder-decoder [17] and attention-based models. The operation of an LSTM is described by the following

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Table 1, LSTMs have disadvantages in terms of intra-sequence parallelism, in that the computation needs to be done sequentially. Although CNN-based end-to-end speech recognition systems have advantages in computational efficiency on embedded processors supporting Single Instruction Multiple Data (SIMD) by exploiting intra-sequence parallelism [15].

Recently, self-attention has been successfully applied to speech recognition. In [14], self-attention mechanism was implemented using a scaled-dot attention described by the following equation:

\[
\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V,
\]

where \(Q, K, \) and \(V\) are matrices representing a query, a key, and a value, and \(d_k\) is the dimension of the key. In a self-attention layer, all of the queries, keys, and values are the outputs of the previous layer.

In Table 1, we compare typical values of memory footprint required for stacks of these neural network layers [15]. These stacks correspond to the neural net layers in Fig. 2a or the encoder portion of Recurrent Neural Network-Transducer (RNN-T) [22, 23] or attention-based models in Fig. 2b and Fig. 2c respectively. In obtaining these values, we assume that the number of layer \(N\) is 6 for the LSTM case [18], and 15 for the CNN and the self-attention cases. For speech recognition, \(L\) is usually a few hundred, while \(T\) is about ten or less. Based on this, we assume that the dimension \(D\) is 2048, the sequence length \(L\) is 100, and the filter length \(T\) is 5, respectively, to calculate typical values [15].

### 3. END-TO-END SPEECH RECOGNITION ARCHITECTURES

Speech recognition is a task of finding the sequence-to-sequence mapping from an input sequence of acoustic features to an output sequence of labels. Let us denote the input and output sequences by \(x_{[0:M]}\) and \(y_{[0:L]}\) as shown below:

\[
x_{[0:M]} = [x_{[0]}, x_{[1]}, \ldots, x_{[M-1]}],
\]

\[
y_{[0:L]} = [y_{0}, y_{1}, y_{2}, \ldots, y_{L-1}],
\]

where \(M\) and \(L\) are the lengths of the input acoustic feature sequence and the output label sequence, respectively. The sequence notation adopted in this paper including (4) follows the Python array slice notation. In this paper, by convention, we use a bracket to
The simplest way of implementing an end-to-end speech recognizer may be employed instead of LSTMs.

Fig. 2 shows structures of end-to-end all neural speech recognition systems. Even though we use a stack of LSTMs in Fig. 2 any kinds of neural network components described in Sec. 2 may be employed instead of LSTMs.

3.1. Connectionist Temporal Classification (CTC)

The simplest way of implementing an end-to-end speech recognizer is using a stack of neural network layers with a Connectionist Temporal Classification loss [24] as shown in Fig. 2a. This model defines a probability distribution over the set of output labels augmented with a special blank symbol, \( \langle \). We define the set of all possible alignments \( \mathcal{B}_{CTC}(x_{[0:M]}, y_{0:L}) \), as the set of all label sequences \( z_{[0,M]} \) where \( z[m] \in Y \cup \langle \), \( 0 \leq m < M \), such that \( z_{[0,M]} \) is identical to \( y_{[0:L]} \) after removing all blank symbols \( \langle \). \( Y \) is the set of the entire alphabet of the output labels. Under this assumption, the posterior probability of the output label sequence is given by the following equation:

\[
P(y_{0:L} | x_{[0:M]}) = \sum_{z_{[0:M]} \in \mathcal{B}_{CTC}(x_{[0:M]}, y_{0:L})} \Pi_{m=0}^{M-1} P(z_{[m]} | x_{[0:M]}).
\]

(5)

The CTC loss is defined by the following equation:

\[
\mathcal{L}_{CTC} = -E \left[ \log P(y_{0:L} | x_{[0:M]}) \right].
\]

(6)

The parameters of a model with the CTC loss are updated using the forward-backward recursion assuming conditional independence [24], which is similar to the forward-backward algorithm used for training Hidden Markov Models (HMMs) [2].

3.2. Recurrent Neural Network-Transducer (RNN-T)

In spite of its simplicity, the model described in Sec. 3.1 has several shortcomings including the conditional independence assumption during the model training [25] and the lack of explicit feedback paths from the output label. An improved version of this model is the RNN-T model [23] shown in Fig. 2b. In this model, there is an explicit feedback path from the output label to the prediction network which plays a similar role to an LM. The probability model of an RNN-T based model is similar to the CTC model:

\[
P(y_{0:L} | x_{[0:M]}) = \sum_{z_{[0:M+L]} \in \mathcal{B}_{RNN-T}(y_{[0:L]}, x_{[0:M]})} \Pi_{m=0}^{M+L-1} P(z_{[m]} | x_{[0:M]}),
\]

(7)

where \( \mathcal{B}_{RNN-T}(x_{[0:M]}, y_{0:L}) \) is the set of all possible label sequences \( z_{[0,M+L]} \) where \( z[u] \in Y \cup \langle \), \( 0 \leq u < M + L \), such that after removing blank symbols \( \langle \) from \( z_{[0,M+L]} \), it becomes the same as \( y_{0:L} \). As in Sec. 3.1, \( Y \) is the set of the entire alphabet of the output labels.

3.3. Attention-based Models

Another popular end-to-end speech recognition approach is employing the attention-mechanism as shown in Fig. 2c [12]. In attention-based approaches, we use the attention between the encoder and decoder hidden outputs. The equation for encoder-decoder attention is basically the same as (3):

\[
ce[m], l = \text{Energy}(h_{[m]}^{enc}, h_{[l]}^{dec}) \quad \text{Energy}(e_{[m]}, l)
\]

(8a)

\[
a[m], l = \text{softmax}(c[m], l)
\]

(8b)

\[
c_l = \sum_{m=0}^{M-1} a[m, l] h_{[m]}^{enc}
\]

(8c)

where \( c_l \) is the context vector which is used as the input to the decoder. \( h_{[m]}^{enc} \) and \( h_{[l]}^{dec} \) are hidden outputs from the encoder at time \( m \) and from the decoder at the label index \( l \) respectively. \( c[m], l \) in (8a) is the energy for the input time index \( m \) and the output label index \( l \).

3.4. Monotonic Chunkwise Attention(MoCha)-based Models

Although the attention-based approach in 3.3 has been quite successful, on-line streaming recognition with this approach has been a challenge. This is because the entire sequence of input features must be encoded before the decoder starts generating the first output label. Several variations of the attention including Monotonic
Chunkwise Attention (MoChA) have been proposed to resolve this problem. In the MoChA model, there are two attention mechanisms: a hard monotonic attention followed by a soft chunkwise attention. The hard monotonic attention is employed to determine which element should be attended from a sequence of hidden encoder outputs $h^{(enc)}_{[m]}$. The hard monotonic attention is obtained from the hidden encoder output $h^{(enc)}_{[m]}$ at the time index $m$ and the hidden decoder output $h^{(dec)}_{l-1}$ at the output label index $l-1$ as follows:

$$
c_{[m], l}^{(mono)} = \text{MonotonicEnergy}(h^{(enc)}_{[m]}, h^{(dec)}_{l-1}) \quad (9a)$$

$$
a_{[m], l}^{(mono)} = \sigma(c_{[m], l}^{(mono)}) \quad (9b)$$

$$
z_{[m], l} \sim \text{Bernoulli}\left(a_{[m], l}^{(mono)}\right), \quad (9c)$$

where $\sigma(\cdot)$ is a logistic sigmoid function and $\text{MonotonicEnergy}$ is the energy function defined as follows [26]:

$$
\text{MonotonicEnergy}(h^{(enc)}_{[m]}, h^{(dec)}_{l-1}) = g_{[v]}^T \tanh(W^{(dec)}_{l-1} h^{(dec)}_{l-1} + W^{(enc)} h^{(enc)}_{[m]} + b) + r, \quad (10)
$$

where $v, W^{(dec)}, W^{(enc)}, b, g$, and $r$ are learnable variables. After finding out the position to attend using $z_{[m], l}$, a soft attention with a fixed chunk size is employed to generate the context vector that will be given as an input to the decoder. We refer readers interested in the more detailed structure of MoChA to [18][26]. A block schematic of an on-device speech recognizer based on MoChA is shown in Fig. 4.

### 3.5. Comparison between MoChA and RNN-T based models

In this section, we compare a MoChA-based model described in Sec. 3.4 with a RNN-T-based model discussed in Sec. 3.2. For these RNN-T and MoChA models, we used the same encoder structures consisting of six LSTM layers with the unit size of 1,024. The lower three LSTM layers in the encoder are interleaved with 2:1 max-pool layers as in [18]. A single LSTM layer with the unit size of 1024 is employed for both the decoder of the MoChA-based model and the prediction network of RNN-T-based model. Training was performed using an in-house training toolkit built with the same Keras [27] and Tensorflow 2.3 APIs [28]. A 40-dimension power-mel feature with a power coefficient of 1/15 [4] is used as the input feature. We prefer the power-mel feature since the power-mel feature shows better speech recognition accuracy [29][30][31]. In Table 2, we compare the performance of MoChA and RNN-T in terms of speech recognition accuracy and latency. The model is compressed by 8-bit quantization and Low Rank Approximation (LRA) [32]. More details about the compression procedure is described in [18]. The latency was measured on a Samsung Galaxy Note 10 device. As shown in this table, the MoChA-based model shows slightly better speech recognition accuracy compared to the RNN-T-based model. However, the RNN-T-based model is noticeably better than the MoChA-based model in terms of latency and consistency of latency. The MoChA-based model shows more variation in latency compared to the RNN-T-based model.

### 4. APPROACHES FOR FURTHER PERFORMANCE IMPROVEMENT

Recently, various techniques have been proposed to further improve the performance of all neural end-to-end speech recognition systems described in Sec. 4. We will discuss some of these techniques in this section.

#### 4.1. Combination with a non-streaming model

Even though Bidirectional LSTMs (BLSTMs) perform significantly better than unidirectional counterparts for on-device applications [18], latency requirement usually prohibits their usage. To get the advantage of BLSTMs without significantly affecting overall latency, we proposed a recognition system combining the streaming MoChA model with a batch full attention model in [33]. The entire
structure of this system is shown in Fig. 4. In this model, there is a shared streaming encoder consisting of uni-directional LSTMs. On one side, the streaming MoChA attention and decoder can generate streaming speech recognition result. On the other side, one backward LSTM layer on top of the shared unidirectional layer comprise a BLSTM layer, which is followed by a full attention model. When the user finishes speaking, then this full attention model generates low-latency batch speech recognition result. The latency impact is relatively small since there is only one layer of backward LSTM layer in the encoder. The experimental result is summarized in Table 3. We use the same model architecture and experiment configuration as described in Sec. 3. As shown in this table, the proposed model in the bottom row shows significantly better result than the MoChA-based model shown in the top row of this table with endurable increase in latency.

Table 3: Word Error Rate (WER) comparison between a streaming model, a non-streaming model, and a streaming model combined with a single layer of backward LSTM followed by a full attention to minimize the impact on latency.

| Model                                      | LibriSpeech test-clean | LibriSpeech test-other |
|--------------------------------------------|------------------------|------------------------|
| Uni-Directional Encoder                    | 6.88 %                 | 19.11 %                |
| + MoChA-Attention                          |                        |                        |
| Bi-Directional Encoder + Full-Attention    | 3.62 %                 | 11.20 %                |
| Shared Uni-Directional Encoder + Full-Atttn| 4.09 %                 | 12.04 %                |

4.2. Shallow-fusion with language models

End-to-end speech recognition models discussed in Sec. 3 are trained using only paired speech-text data. Compared to traditional AM-LM approaches where an LM is often trained using a much larger text corpus possibly containing billions of sentences [34], the end-to-end speech recognition model sees much limited number of word sequences during the training phase. To get further performance improvement, researchers have proposed various techniques of incorporating external language models such as shallow-fusion [35], deep-fusion [36], and cold-fusion [37]. Among them, in spite of its simplicity, shallow-fusion seems to be more effective than other approaches [38]. In shallow-fusion, the log probability from the end-to-end speech recognition model is linearly interpolated with the probability from the language model as follows:

\[
\log p_d (y_t | x_{[0:n_t]}) = \log p (y_t | x_{[0:n_t]}, \hat{y}_{0:t}) + \lambda \log p_m (y_t | \hat{y}_{0:t})
\]

where \( p_m (y_t | \hat{y}_{0:t}) \) is the probability of predicting the label \( y_t \) from the LM, and the \( p (y_t | x_{[0:n_t]} \) is the posterior probability obtained from the end-to-end speech recognition model.

Shallow-fusion with an LM is helpful in enhancing speech performance in general domains, thus, most of the state of the art speech recognition results on publicly available test sets (e.g. LibriSpeech [39]) are obtained with this technique [8, 29, 40]. In addition to this, this technique is also very useful for enhancing performance in special domain like personal names, geographic names, or music names by employing domain-specific LMs. In case of n-gram LMs, they can be easily built on-device to support personalized speech recognition [18]. For on-device command recognition, shallow-fusion with a WFST is also useful for specific domains since WFST contains a list of words not just subword units [41].

4.3. Improving NER performance using a spell corrector

Even though end-to-end all neural speech recognition systems have shown quite remarkable speech recognition accuracy with small memory footprint, it has been frequently observed that performance is poorer in recognizing named entities [42]. Compared to conventional speech recognizers built with a WFST containing dictionary information, an end-to-end speech recognition system does not explicitly contain a list of named entities. Therefore, the speech recognition accuracy of such systems is generally low for specialized domains handling song names, composers’ names, personal names, and geographical names. Without dictionary information, spelling errors may also occur with all neural speech recognizers. This named entity recognition issue can be somewhat relieved by applying shallow-fusion with an LM as described in Sec. 4.2. However, more drastic performance improvement is usually obtained by classifying the domain from the speech recognition output and applying spell correction using a list of named entities found in that domain. In [41], a multi-stage spell correction approach was proposed to handle a large list of named entities with on-device speech recognizers.

5. COMPRESSION

To run speech recognition models on embedded processors with limited memory, we often need to further reduce the parameter size in order to satisfy computational cost and memory footprint requirements. There are many known techniques to reduce the model size such as quantization, factorization, distillation, and pruning. The simplest way of accomplishing compression may be applying 8-bit quantization, which is supported by TensorFlowLite™. Several commercially available speech recognition systems [18, 19] have been built using this technique. In feed-forward neural networks, 2-bit or 3-bit quantization has been successfully employed [43]. However, for general purpose processors, there are relatively small gains in going below 8-bit quantization, since Arithmetic Logic Units (ALUs) usually do not support sub-8-bit arithmetic. Another popular technique in reducing the model size of LSTMs is applying Low Rank Approximation (LRA) [44]. As an example, the DeepTwist algorithm, which is based on LRA, is employed to reduce the parameter size in our previous work [18, 41]. More specifically, we were able to reduce the size of MoChA-based models from 531 MB to less than 40 MB without sacrificing the performance using 8-bit quantization and LRA. Pruning may be a good choice if hardware supports sparse matrix arithmetic. In [45], authors propose a three-stage pipeline: pruning, trained quantization and Huffman coding, that work together to reduce the storage requirement of neural networks by 35x to 49x without affecting their accuracy. In [46], the authors studied effectiveness of different compression techniques for end-to-end speech recognition models. They conclude that pruning is the most effective with proper hardware support. In the absence of this, for small models, distillation appears to be the best choice, while factorization appears to be the best approach for larger models.

6. CONCLUSIONS

In this paper, we reviewed various end-to-end all neural automatic speech recognition systems and their optimization techniques for
on-device applications. On-device speech recognition has huge advantages compared to the server-side ones in terms of user privacy, operation without internet, server-cost, and latency. To operate speech recognition systems on embedded processors, we need to consider several factors such as recognition accuracy, computational cost, latency, and the model size. We compared pros and cons of different neural network components such as Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and attention mechanism. We explained and compared different end-to-end neural speech recognition architectures such as a stack of LSTM layers with the Connectionist Temporal Classification (CTC) loss [24]. Recurrent Neural Network-Transformer (RNN-T) [22, 23], attention-based models, and models based on Monotonic Chunk-wise Attention (MoChA) [26]. Further improvement is achieved by combining a streaming model with a low-latency non-streaming model, by applying shallow-fusion with a Language Model (LM), and by applying spell correction using a list of named entities [47]. We also discussed several model compression techniques including quantization, singular value decomposition, pruning, and knowledge distillation. These recent advances in all neural end-to-end speech recognition make it possible to commercialize all neural on-device end-to-end speech recognition systems [18, 19, 41].

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