STREAMING END-TO-END SPEECH RECOGNITION WITH JOINTLY TRAINED NEURAL FEATURE ENHANCEMENT

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ABSTRACT

In this paper, we present a streaming end-to-end speech recognition model based on Monotonic Chunkwise Attention (MoCha) jointly trained with enhancement layers. Even though the MoCha attention enables streaming speech recognition with recognition accuracy comparable to a full attention-based approach, training this model is sensitive to various factors such as the difficulty of training examples, hyper-parameters, and so on. Because of these issues, speech recognition accuracy of a MoCha-based model for clean speech drops significantly when a multi-style training approach is applied. Inspired by Curriculum Learning [1], we introduce two training strategies: Gradual Application of Enhanced Features (GAEF) and Gradual Reduction of Enhanced Loss (GREL). With GAEF, the model is initially trained using clean features. Subsequently, the portion of outputs from the enhancement layers gradually increases. With GREL, the portion of the Mean Squared Error (MSE) loss for the enhanced output gradually reduces as training proceeds. In experimental results on the LibriSpeech corpus and noisy far-field test sets, the proposed model with GAEF-GREL training strategies shows significantly better results than the conventional multi-style training approach.

Index Terms: end-to-end speech recognition, data augmentation, monotonic chunkwise attention, attention-based encoder-decoder, acoustic simulator

1. INTRODUCTION

Since the introduction of end-to-end all neural speech recognition models [2], there have been growing interests in these models. These models have significant advantages in structural simplicity and simplified inference to generate texts. Compared to the conventional speech recognition system consisting of multiple discrete components such as an Acoustic Model (AM), a Language Model (LM), a pronunciation dictionary, and a decoder based on a Weighted Finite State Transducer (WFST), a complete end-to-end all neural speech recognition system realizes all these functionalities using a single-structured neural network. Further improvements in these end-to-end speech recognition systems have been obtained thanks to a better choice of target units such as Byte Pair Encoded (BPE) and unigram language model [3] units, improved training methodologies, and so on. Another major advantage of these end-to-end models is that they require much smaller memory footprint compared to the conventional WFST-based models, which enables their widespread use for on-device applications [4,5].

Attention-based Encoder-Decoder (AED) is perhaps the most well-known type of such end-to-end speech recognition systems [2]. Recently, it has been reported that the performance of the AED system outperforms the conventional WFST-based decoders for large vocabulary speech recognition tasks [6]. In spite of these achievements in performance, the biggest shortcoming of the AED-based speech recognition system is its lack of streaming capability. To overcome this restriction, several variations of AED approaches including Monotonous Chunkwise Attention (MoCha) have been proposed [7]. In our previous work [4], we successfully employed MoCha-based model for on-device dictation applications.

Recently, speech recognition has been widely adopted for AI speakers [8] and home appliance devices [5]. Therefore, far-field speech recognition has become increasingly more important. It has been observed that various kinds of data augmentation [9] or approaches motivated by auditory processing [10] is especially helpful for far-field noisy environments. On-the-fly data augmentation using an acoustic simulator [8,11] has been especially successful for these far-field speech recognition scenarios. When data augmentation using an acoustic simulator is employed for full-attention models, we observe that it even enhances performance for clean utterances perhaps because of better regularization as will be shown in Sec. 3. However, the MoCha attention is generally unstable compared to the full attention [12]. Therefore, it has been very difficult to obtain good speech recognition accuracy if the same data augmentation strategy is directly applied to MoCha training, as will be also shown in Sec. 4.

In this work, we place an enhancement block consisting of two layers of Long Short-Term Memories (LSTMs) in front of the streaming MoCha speech recognition model. We refer this model to as Neural Enhancement-Automatic Speech Recognition (NE-ASR). This combined model is jointly trained from scratch using random initialization without any needs to train each sub-model separately beforehand. Even though there have been many attempts to jointly optimize an enhancement block along with a speech recognition model, our approach is unique in the following two aspects:

- Gradual Application of Enhanced Feature (GAEF)
- Gradual Reduction of Enhancement Loss (GREL)

To the best of our knowledge, our work is the first attempt in gradually reducing the enhancement loss in the joint training of the entire models which has the net effect of gradually combining two separate enhancement and encoder blocks into a single combined encoder block. As will be shown in Sec. 4 this GREL strategy significantly enhances speech recognition performance. This NE-ASR model shows improved performance compared to the baseline MoCha model for LibriSpeech [13] test-clean and test-other, and significantly better performance than the conventional data augmentation technique on the same test set. For re-recorded far-field noisy test sets, our approach reduces Word Error Rates (WERs) relatively by 55.93 % and 12.36 % over the baseline and the multi-style trained MoCha models, respectively.

In this paper, we present a streaming end-to-end speech recognition model based on Monotonic Chunkwise Attention (MoCha) jointly trained with enhancement layers. Even though the MoCha attention enables streaming speech recognition with recognition accuracy comparable to a full attention-based approach, training this model is sensitive to various factors such as the difficulty of training examples, hyper-parameters, and so on. Because of these issues, speech recognition accuracy of a MoCha-based model for clean speech drops significantly when a multi-style training approach is applied. Inspired by Curriculum Learning [1], we introduce two training strategies: Gradual Application of Enhanced Features (GAEF) and Gradual Reduction of Enhanced Loss (GREL). With GAEF, the model is initially trained using clean features. Subsequently, the portion of outputs from the enhancement layers gradually increases. With GREL, the portion of the Mean Squared Error (MSE) loss for the enhanced output gradually reduces as training proceeds. In experimental results on the LibriSpeech corpus and noisy far-field test sets, the proposed model with GAEF-GREL training strategies shows significantly better results than the conventional multi-style training approach.

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1. INTRODUCTION

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2. RELATED WORKS

2.1. Monotonic Chunkwise Attention

In this section, we briefly describe the Monotonic Chunkwise Attention (MoCha) algorithm [7]. 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 frame index $m$ and the hidden decoder output $h_{i-1}^{dec}$ at the output label index $i - 1$ as follows:

$$e_i^{mono}[m] = MonotonicEnergy(h^{enc}[m], h_{i-1}^{dec})$$  \hspace{1cm} (1a)  

$$a_i^{mono}[m] = \sigma(e_i^{mono}[m])$$  \hspace{1cm} (1b)  

$$z_i[m] \sim Bernoulli(a_i^{mono}[m])$$  \hspace{1cm} (1c)

where $\sigma(\cdot)$ is a logistic sigmoid function and $MonotonicEnergy$ is the energy function defined as follows [7]:

$$MonotonicEnergy(h^{enc}[m], h_{i-1}^{dec}) = g \frac{v^T}{|v|} \tanh(W_{dec}[h_{i-1}^{dec}] + W_{enc}h^{enc}[m] + b) + r$$  \hspace{1cm} (2)

where $v, W_{dec}, W_{enc}, b, g,$ and $r$ are learnable variables. After finding out the position to attend using (1c), 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. For all model training in this paper, an Adam optimizer [14] is employed. We observe that careful learning rate scheduling is required to train high-performing MoCha models. In this work, we employ a pre-training stage similar to that in our previous work [8]. During the pre-training stage, when a new layer is added or the pool size of a max-pooling layer is changed, the learning rate is lowered to 1.0e-4 and linearly increased to 3.0e-4. In LibriSpeech training described in Sec. 2, this pre-training stage continues up to 2.25 epochs. After the pre-training stage, the learning rate is maintained at 3.0e-4 up to the eight full epochs. After finishing eight epochs of training, the learning rate is reduced using the Newbob method. Without careful learning rate control, MoCha model does not converge well especially when far-field data augmentation is applied to the training set.

2.2. Data augmentation using an acoustic simulator

The acoustic simulator we used in our joint-training strategy is based on the structure described in our earlier works [8][11][15]. Our acoustic simulator is designed to simulate the general case with J sound sources and J microphones in a cuboid-shaped room with acoustically reflective walls [15]. However, for brevity, we consider a single microphone case in this paper. The relationship between the sound source $x_0[n]$ and the microphone output $s[n]$ is given by the following equation:

$$s[n] = h_0[n] * x_0[n] + \sum_{i=1}^{j-1} \alpha_i h_i[n] * x_i[n],$$ \hspace{1cm} (3)

where $x_i[n]$ is the signal from the i-th source. $\alpha_i$ and $h_i[n]$ are the scaling coefficient and the room impulse response associated with each sound source. When the image method is employed, the room impulse response $h_i[n]$ is given by the following equation [15]:

$$h_i[n] = \sum_{k=0}^{\infty} e^{g_{j,k}} d_k \left[n - \frac{d_{j,k} f_s}{c_0} \right],$$ \hspace{1cm} (4)

where $d_{i,k}$, $T_{i,k}$, $g_{i,k}$, $f_s$, and $c_0$ are the distance between the microphone and the sound source image, the reflection coefficient of the wall, the number of reflections in the acoustic path connecting the microphone and the sound source image, the sampling rate of a signal, and the speed of sound in the air, respectively. In this work, we employ a similar configuration to our previous work [8] regarding the distribution of room sizes, reverberation times ($T_{60}$), Signal-to-Noise Ratios in Decibel (SNR dB), sound source locations and so on.

3. JOINT-TRAINING STRATEGY

3.1. Neural Enhancement - Automatic Speech Recognition (NE-ASR) model

In this section, we explain our joint training strategy of enhancement and speech recognition models in detail. The entire structure of the Neural Enhancement and Automatic Speech Recognition (NE-ASR) model is shown in Fig. 1. This NE-ASR model structure does not change during the training phase. However, since we gradually reduce the weight for the enhancement loss $\lambda$ and the weight $w$ for the normalized clean feature to zero as training proceeds, the structure is finally equivalent to the model in Fig. 1 (b).

$s[n]$ at the bottom of Fig. 1 is the clean speech signal with $n$ being the sample index. Using the acoustic simulator described in Sec. 2.2 [8][16], we obtain simulated far-field noisy utterances $s^{aug}[n]$.

For on-the-fly data augmentation, we use the example server system described in [11]. As will be discussed in Sec. 3.4, there is a mismatch in time-delay and energy between the augmented signal $s^{aug}[n]$ and the original signal $s[n]$. This mismatch is compensated using the Delay-Energy Normalization (DEN) block. This DEN block is introduced because we believe that the neural network cannot be trained effectively to learn the mapping from noisy features to clean features if the time delay or the energy level difference vary randomly.

The output from the DEN block is represented by $\hat{s}[n]$ in Fig. 1. We use power-mel features of the order of 40 [16][17], which is motivated by the power-law nonlinearity with a power coefficient of 1/15 [18]. We use a window length of 25 ms with the period between successive windows of 10 ms. We use power-mel features instead of the more widely used log-mel features since power-mel features have shown better performance in our previous studies [16][17]. We obtain power-mel features $x^{aug}[n]$ and $\hat{x}[n]$ from the augmented and the normalized clean speech signals respectively with $m$ being the frame index. The enhancement layers in Fig. 1 consist of two layers of LSTM. The unit sizes of these two layers are 1024 and 40 respectively. The enhanced feature $x^{enh}[n]$ is obtained as the output of the enhanced layers, and the linear combination of the enhanced feature $x^{enh}[n]$ and the normalized clean feature $\hat{x}[n]$ is used as the input to the MoCha based streaming end-to-end speech recognition model. This feature combination will be described in detail in the following Sec. 3.2. In the MoCha model, the encoder consists of six layers of uni-directional LSTMs with the unit size of 1536 that are interleaved with 2:1 max-pooling layers in the lower three layers as in [4]. Thus, the overall temporal reduction factor is 8:1.
3.2. Gradual application of enhanced features (GAEF)

In machine learning, it has been frequently observed that models are trained more effectively if they are trained with easier examples in the early stage of training [1]. Motivated by this observation, we start training the NE-ASR model with easier examples $\hat{x}[m]$. In the initial stage of training, the output from the enhancement block $x^{\text{enh}}[m]$ might be still noisy, since this enhancement layers are not sufficiently trained. The input to the MoCha speech recognition model $x^{\text{comb}}[m]$ is a linear combination of the enhanced feature $x^{\text{enh}}[m]$ and the normalized clean feature $x[m]$ that is given by the following equation:

$$x^{\text{comb}}[m] = (1 - w)x^{\text{enh}}[m] + w\hat{x}[m],$$

where $w$ is the weighting coefficient. As the training proceeds, the $w$ decreases linearly from one to zero. In our experiments with LibriSpeech training in Sec. 4 [4] $w$ becomes zero after eight full epochs of training.

3.3. Gradual reduction of enhancement loss (GREL)

The loss function $L$ that we used in this joint training is a combination of the Cross-Entropy (CE) loss $L_{\text{CE}}$, Connectionist Temporal Classification (CTC) loss $L_{\text{CTC}}$ [19] and the Mean Squared Error (MSE) loss, which is given by the following equation:

$$L = L_{\text{CE}} + L_{\text{CTC}} + \lambda L_{\text{MSE}},$$

where $\lambda$ : $1.0 \rightarrow 0.0$ as training proceeds.

The CTC loss $L_{\text{CTC}}$ and the CE loss $L_{\text{CE}}$ are computed from the softmax outputs from the encoder and the decoder respectively, as shown in Fig. 1(a) [20]. The MSE loss is computed from the enhancement layer output $x^{\text{enh}}[m]$ using the normalized clean feature $\hat{x}[m]$ as the target. Similar to the case of GAEF in Sec. 3.2, in our experiments with LibriSpeech training in Sec. 4 [4] $\lambda$ value is one at the beginning of training and linearly reduces to zero after finishing eight epochs of training.

3.4. Delay-Energy Normalization (DEN)

In this section, we describe delay-energy normalization employed to obtain the normalized speech signal $s[n]$ in Fig. 1. From (7), assuming that $x_0[n] = s[n]$ is the target sound source and the remaining sound sources $x_i[n], 1 \leq i \leq I - 1$ are noise sound sources, this equation expressed as follows:

$$s^{\text{aug}}[n] = h_0[n] + s[n] + \nu[n],$$

where $\nu[n]$ is the combined noise-terms in (7) defined by $\sum_{i=1}^{I-1} \alpha_i h_i[n] * x_i[n]$. From (7), we observe that $s^{\text{aug}}[n]$ has delays compared to the target signal $x_0[n]$ because of the room impulse response $h_0[n]$. From (8), we observe that the first arriving impulse response is delayed by $L_{\text{CTC}} / s$. Thus, in the DEN block, this amount of delay component is added to the clean speech. The energy of $y[n]$ also may be very different from that of $s[n]$. We measure the 95-percentile of frame energies of $s^{\text{aug}}[n]$, and $s[n]$ is scaled to have the same 95-percentile of frame energies.

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**Fig. 1:** The joint training strategy for a combination of neural enhancement and an end-to-end speech recognition: The initial training pipeline is shown in Fig. 1(a). $\lambda$ is a weight for the Mean Squared Error (MSE) loss $L_{\text{MSE}}$ in (9). $w$ is a weight for the normalized clean feature $\hat{x}[m]$ in (5). As training proceeds, $\lambda$ and $w$ reduce to zero, which transfigures the training pipeline into the one in Fig. 1(b).
In this section, we present speech recognition results obtained using the NE-ASR model on the LibriSpeech database [13] and in-house far-field noisy test set. For training, we used the entire 960 hours LibriSpeech training set consisting of 281,241 utterances. For evaluation, we used the official 5.4 hours test-clean and 5.1 hours test-other sets. To evaluate the performance on far-field noisy environments, re-recording was done by playing back 100 command utterances using a loud speaker at 5-meter distance in a real room. The reverberation time in this room was measured to be $T_{60} = 430$ ms. We simulated far-field additive noise by playing back four different types of noise using loud speakers: babble, music, two different types of noise using a loudspeaker at 5-meter distance in a real room.

Table 1 shows the speech recognition experimental results using three different models. To implement and train this model, we use the Keras framework [21] with the Tensorflow 2.3 toolkit. For all the cases in Table 1, the models are trained twice up to 25 full epochs and these two WERs are averaged. During the inference for evaluation, we use the beam size of 12. The BFA stands for Bidirectional LSTMs (BLSTMs) in the encoder with a Full Attention (BFA), which has a similar structure to those our previous work [16][17]. For MoCha and NE-ASR models, we use Unidirectional LSTMs (ULSTMs) with the MoCha attention for streaming speech recognition. The unit sizes of the BLSTM and ULSTM in the encoder is 1024 and 1536, respectively. For all these three models, a single layer of ULSTM of a unit size of 1000 is employed for the decoder part. As shown in this Table, in the case of BFA, the performance for all these three test sets improve by applying on-the-fly data augmentation using the acoustic simulator [11]. We note that augmentation using noisy utterances even enhances performance on the test-clean test set perhaps because of better regularization. However in the case of the MoCha model, after applying the same data augmentation, the performance on the test-clean test set degrades by 14.65 % relatively even with a very careful learning rate schedule mentioned in Sec. 2.1. Without careful learning rate scheduling, the model even does not converge. In the case of the NE-ASR model, GREL strategy significantly improves the performance compared to the MoCha model with the far-field data augmentation. GAEF itself does not show performance improvement when it is employed without GREL. However, when we employ both of the GAEF and GREL algorithms, the best performance is achieved. As shown in Table 1 the DEN approach brings further improvement. Overall, the NE-ASR model with the GAEF-GREL training strategy shows significantly better results than the conventional data augmentation technique with relative improvements of 18.45 %, 4.81 %, and 12.36 % on the LibriSpeech test-clean, test-other and the re-recorded far-field noisy test sets respectively.

### Table 1: Word Error Rates (WERs) using three different neural network models on the LibriSpeech corpus and the far-field noisy test set.

| Model Type       | Training Strategy | Noise Types   |
|------------------|-------------------|---------------|
|                  | Far-field Data Augmentation | GAEF | GREL | LibriSpeech test-clean | LibriSpeech test-other | Far-Field Noisy |
| BLSTM with Full Attention (1024 LSTM unit size) | X | - | - | 4.19 % | 13.95 % | 70.22 % |
| ULSTM with MoCha (1536 LSTM unit size) | X | - | - | 6.06 % | 17.90 % | 78.83 % |
| NE-ASR without DEN | O | X | X | 8.01 % | 19.43 % | 43.79 % |
| NE-ASR with DEN  | O | O | X | 6.99 % | 19.35 % | 45.61 % |
|                  | O | O | O | 5.98 % | 15.70 % | 35.35 % |

### 4. EXPERIMENTAL RESULTS

In this section, we present speech recognition results obtained using the NE-ASR model on the LibriSpeech database [13] and in-house far-field noisy test set. For training, we used the entire 960 hours LibriSpeech training set consisting of 281,241 utterances. For evaluation, we used the official 5.4 hours test-clean and 5.1 hours test-other sets. To evaluate the performance on far-field noisy environments, re-recording was done by playing back 100 command utterances using a loud speaker at 5-meter distance in a real room. The reverberation time in this room was measured to be $T_{60} = 430$ ms. We simulated far-field additive noise by playing back four different types of noise using loud speakers: babble, music, two different types of noise using a loudspeaker at 5-meter distance in a real room. We created noisy utterances at five different SNR dB levels: 0-dB, 5-dB, 10-dB, 15-dB, and 20-dB. This far-field noisy test set was previously used in our work described in [11].

Table 1 shows the speech recognition experimental results using three different models. To implement and train this model, we use the Keras framework [21] with the Tensorflow 2.3 toolkit. For all the cases in Table 1, the models are trained twice up to 25 full epochs and these two WERs are averaged. During the inference for evaluation, we use the beam size of 12. The BFA stands for Bidirectional LSTMs (BLSTMs) in the encoder with a Full Attention (BFA), which has a similar structure to those our previous work [16][17]. For MoCha and NE-ASR models, we use Unidirectional LSTMs (ULSTMs) with the MoCha attention for streaming speech recognition. The unit sizes of the BLSTM and ULSTM in the encoder is 1024 and 1536, respectively. For all these three models, a single layer of ULSTM of a unit size of 1000 is employed for the decoder part. As shown in this Table, in the case of BFA, the performance for all these three test sets improve by applying on-the-fly data augmentation using the acoustic simulator [11]. We note that augmentation using noisy utterances even enhances performance on the test-clean test set perhaps because of better regularization. However in the case of the MoCha model, after applying the same data augmentation, the performance on the test-clean test set degrades by 14.65 % relatively even with a very careful learning rate schedule mentioned in Sec. 2.1. Without careful learning rate scheduling, the model even does not converge. In the case of the NE-ASR model, GREL strategy significantly improves the performance compared to the MoCha model with the far-field data augmentation. GAEF itself does not show performance improvement when it is employed without GREL. However, when we employ both of the GAEF and GREL algorithms, the best performance is achieved. As shown in Table 1 the DEN approach brings further improvement. Overall, the NE-ASR model with the GAEF-GREL training strategy shows significantly better results than the conventional data augmentation technique with relative improvements of 18.45 %, 4.81 %, and 12.36 % on the LibriSpeech test-clean, test-other and the re-recorded far-field noisy test sets respectively.

### 5. CONCLUSIONS

In this paper, we present a Neural Enhancement-Automatic Speech Recognition (NE-ASR) model that consists of an enhancement model and an end-to-end speech recognition model. These two models are jointly trained from scratch using random initialization without pre-training each model separately. Inspired by Curriculum Learning [1], we propose two training strategies in this work: Gradual Application of Enhanced Feature (GAEF) and Gradual Reduction of Enhancement Loss (GREL). With GAEF, training initially starts using clean training features. Subsequently the portion of outputs from the enhancement block gradually increases. With GREL, the Mean Squared Error (MSE) loss for the enhanced output gradually reduces as training proceeds. In experimental results on the LibriSpeech test-clean, test-other [22], and the re-recorded far-field noisy test sets, the NE-ASR model with GAEF-GREL training strategies shows significantly better results than the conventional data augmentation technique with relative improvements of 18.45 %, 4.81 %, and 12.36 % respectively. It has been very difficult to maintain the speech recognition accuracy on clean speech with a MoCha-based model when data augmentation is done using the acoustic simulator to enhance far-field noisy performance [3]. However, using the NE-ASR model with GAEF-GREL training strategies, the performance on LibriSpeech test-clean and test-other sets is even substantially better than the baseline MoCha model without noticeable training stability issues.
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