Convolutional Recurrent Neural Network Based Progressive Learning for Monaural Speech Enhancement

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Abstract

Recently, progressive learning has shown its capacity to improve speech quality and speech intelligibility when it is combined with deep neural network (DNN) and long short-term memory (LSTM) based monaural speech enhancement algorithms, especially in low signal-to-noise ratio (SNR) conditions. Nevertheless, due to a large number of parameters and high computational complexity, it is hard to implement in current resource-limited micro-controllers and thus, it is essential to significantly reduce both the number of parameters and the computational load for practical applications. For this purpose, we propose a novel progressive learning framework with causal convolutional recurrent neural networks called PL-CRNN, which takes advantage of both convolutional neural networks and recurrent neural networks to drastically reduce the number of parameters and simultaneously improve speech quality and speech intelligibility. Numerous experiments verify the effectiveness of the proposed PL-CRNN model and indicate that it yields consistent better performance than the PL-DNN and PL-LSTM algorithms and also it gets results close even better than the CRNN in terms of objective measurements. Compared with PL-DNN, PL-LSTM, and CRNN, the proposed PL-CRNN algorithm can reduce the number of parameters

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up to 93%, 97%, and 92%, respectively.

Keywords: speech enhancement, deep learning, progressive learning, convolutional neural network, long short-term memory

1. Introduction

Environmental noise is one of the major factors that have significant influences on robust automatic speech recognition (ASR), speech communication system and hearing implants [1]. To improve speech recognition accuracy and speech communication quality in real scenarios, speech enhancement algorithms are proposed to extract the desired speech from its noisy equivalent to improve signal-to-noise ratio (SNR). Conventional monaural speech enhancement methods include spectral subtraction [2], Wiener filtering [3], subspace-based methods [5], and so on. It is well-known that the performance of these methods usually suffers from heavily decreased performance in extremely low SNR and non-stationary noise conditions, and it has already shown that these conventional speech enhancement algorithms cannot improve speech intelligibility for normal-hearing (NH) listeners [7].

In recent years, deep neural network (DNN)-based speech enhancement algorithms have attracted wide attention and their improved versions have been investigated owing to its superior potentials in complicated nonlinear mapping problems. DNN-based monaural speech enhancement algorithms are often categorized into two types, where one is the spectral mapping approach [8] and the other is the mask mapping approach [11], which includes ideal binary mask (IBM) [14], ideal ratio mask (IRM) [15], ideal amplitude mask (IAM) [13] and complex domain-based mask [12]. In the previous fully connected (FC)-based noise reduction approaches, noisy features, and clean labels are extracted in the frame format so that speech is enhanced frame by frame. Because of neglecting the structural characteristics of speech spectra and long contexts relations between adjacent frames, these approaches often result in spectral artifacts and speech distortion in high-frequency bands. To resolve these problems, convolu-
tional neural network (CNN)-based and recurrent neural network (RNN)-based models are recently investigated in the literature [10, 16, 17, 18, 19], which have achieved better performance in both noise reduction and speech distortion. More recently, a type of advanced network named convolutional recurrent neural networks (CRNN) is proposed, which takes advantage of both CNNs and RNNs. Compared with the single-type network, previous experiments have shown that CRNN obtains better speech enhancement results [20, 24].

Progressive learning (PL) has been introduced to the supervised speech enhancement algorithms [21, 22]. Essentially, it can be regarded as a type of curriculum learning problem. Different from directly mapping from noisy features to clean targets, the whole process stage is divided into multiple easier and smaller stages, where the previous stages can boost the subsequent training processes. In [21], the whole stage is divided into multiple stages so that within each stage, its target is to improve SNR to some degrees instead of directly recovering clean speech. FC is utilized for training in each stage. In [22], LSTM is utilized as the principal layer, which can make full use of long-short time dependencies to obtain more spectral information. Note that, different from PL-DNN, dense connection is implemented in adjacent stages, which is helpful to improve the performance by effectively aggregating the information in different stages. For simplicity, architectures in the literature [21, 22] are referred as PL-DNN and PL-LSTM, respectively.

This paper introduce a progressive learning model to improve the performance of CRNN, which can also significantly reduce its computational complexity and its number of parameters simultaneously. The proposed algorithm has several innovations when compared with previous works. First, causal CRNN is adopted as the sub-model within each stage instead of FC layers or LSTM layers. This is because CRNN is more parameter-efficient than LSTM [24] and is capable for real-time applications due to the fact that no future information is involved. Second, different from simply stacking independent and identical sub-net in each stage, the parameter sharing scheme is adopted, which can dramatically decrease the number of parameters while improving the performance.
in the regression task [31]. It is of vital importance for practical application and therefore, higher parameter efficiency can be achieved than previous networks. Finally, two training targets are chosen to study their influence on the performance of speech enhancement.

The remainder of this paper is organized as follows. In Section 2, the system flowchart is introduced briefly. Section 3 describes the training targets, and the CRNN-based model and its combination with progressive learning are also presented in this section. Section 4 presents the experimental settings. Section 5 gives the experimental results. The conclusion is presented in Section 6.

2. PROBLEM FORMULATION AND SYSTEM OVERVIEW

In the time domain, a mixture signal is typically modeled as

\[ x(t) = s(t) + n(t) , \]

where \( x(t) \), \( s(t) \) and \( n(t) \) refer to the noisy, the clean and the noise signals, respectively, in the time index \( t \). From the perspective of frequency domain, the formula can be transformed into

\[ X(k,l) = S(k,l) + N(k,l) , \]

where \( X(k,l) \), \( S(k,l) \) and \( N(k,l) \) denote the noisy, the clean and the noise components, respectively, at the frequency bin index \( k \) and the time frame index \( l \). Monaural speech enhancement aims to extract the clean speech component from the observed noisy mixture. For spectral mapping-based approaches, the output is the estimated clean speech spectral magnitude, which is denoted as \( |\hat{S}(k,l)| \), where \( \hat{\cdot} \) is used here to discriminate between the estimated and clean variables. For mask mapping-based approaches, mask \( \hat{M}(k,l) \) is estimated and can be used to estimate the clean speech spectral magnitude by multiplication operation.

The block diagram of progressive learning is shown in Figure 1. In the training phase, clean speech signals and interference signals are mixed under various SNR conditions, where feature extraction and target calculation are followed. One can see that we use \( |X(k,l)| \) to denote the feature and \( |S_q(k,l)| \)
with $q = 1 \ldots Q$ to denote the target as an example. Here $Q$ is the number of stages. We adopt two types of targets herein, namely, the magnitude of the spectrum and the mask. The targets under different SNR-levels are sent to the deep learning model for training. In the testing phase, noisy features from the test dataset are fed into the well-trained deep learning model to estimate the desired targets in each T-F unit at different stages. After the speech spectral magnitude is estimated, the time-domain speech signal can be reconstructed with an overlap-add (OLA) technique.

![Block diagram of progressive learning](image)

**Figure 1:** The block diagram of progressive learning.

### 3. ARCHITECTURE

#### 3.1. Features and Targets

In this study, two targets are considered, where one is the target magnitude spectrum (TMS) and the other is the ideal amplitude mask (IAM) with signal approximation (SA), which are illustrated in Figure 2. Note that the noisy speech spectrum is also plotted as a reference. SA was introduced to directly
optimize the source separation objective, which leads to reconstruct the speech signal in a best possible way \[25\]. With SA, time-frequency (T-F) mask is estimated as the network output, which is subsequently multiplied with the corresponding noisy spectrum to obtain the estimated clean speech spectrum. While loss is then calculated between the estimated clean speech spectrum and the clean speech spectrum. Experiments have shown that SA often leads to better objective performance than direct mask optimization. To improve the training stability, we constrain the value of mask to range from 0 to 1 and the sigmoid function is chosen as the output nonlinearity accordingly. For TMS, as it is always non-negative, so the softplus function is adopted as the output activation function \[32\]. IAM with SA can be given by
\[
M(k,l) = \min \left\{ \max \left\{ \frac{|S(k,l)|}{X(k,l)}, 0 \right\}, 1 \right\},
\]
\[
SA(k,l) = \left[ S(k,l) - X(k,l) \widehat{M}(k,l) \right]^2.
\]

Figure 2: Illustration of input and targets: (a) the spectrum of noisy speech, (b) ideal amplitude mask, (c) target magnitude spectrum. The training targets (b) and (c) are calculated under 0dB condition, where the noisy speech is a mixture of a clean speech utterance taken from the TIMIT dataset and a factory noise taken from the NOISEX92 database.

3.2. Causal Convolutional Recurrent Neural Network

Causal CRNN is adopted as the sub-net in each stage. It resembles the architecture in \[24\] in which the principal part is the causal convolutional encoder-decoder (CED) with LSTM playing as a bottleneck layer to capture time dependencies. In the encoding part, the size of the feature map gradually decreases
layer by layer, while in the decoding part the size gradually increases, indicating the compression and the extension of features.

Causal mechanism is applied for all the convolutional layers, which is first introduced in [26] for generating raw audio waveform and it achieves state-of-the-art performance than all the previous models. During the calculation of the causal convolution, the predicted outputs do not use any future information and only the past temporal information is involved, and thus it is feasible for real-time processing applications.

RNNs with gated mechanism and long short-term memory have been proposed to mitigate gradient vanishing and exploding issues when learning long time sequences. LSTM is a type of typical memory unit, where different gates are set to control the percentage of saving, dropping temporal information and receiving incoming information.

3.3. Proposed Architecture

Figure 3 plots the architecture of PL-CRNN. The pipeline is comprised of multiple sub-nets, each of which is a type of causal CRNN but with much fewer parameters. The reason for utilizing fewer parameter within each stage is that PL is capable of compensating for the performance gap when a simplified network is adopted instead of the network with a larger number of parameters, which will be further analyzed in Section 5. The number of stages needs to be carefully chosen. This is because PL is expected to improve the performance, but too many learning stages may deteriorate the speech quality due to the information loss when deeper network is trained. Besides, more parameters are necessary with the increase of the number of stages. As shown in [22], $Q = 3$ is chosen due to that it can achieve a good trade-off between the performance and the number of parameters for PL-LSTM.

Within each stage, there are three main components, including the convolutional encoder, the LSTM bottleneck, and the convolutional decoder. For the encoding part, it consists of five convolutional blocks, which creates a compressed and deep representation of the input features by halving the size of
Figure 3: The architecture of proposed progressive learning framework. Different modules are identified with different color blocks as shown at the bottom of the figure. Dashed line indicates the skip operation.

feature dimensions with striding operation in the frequency axes and doubling the number of channels layer. Each of the convolutional layer is followed by batch normalization (BN) [27] and exponential linear unit (ELU) [28]. The decoder is the symmetric representation compared with the encoder, where the size of the frequency feature gradually increases by applying deconvolution [29] and the number of channels decreases layer by layer.

As shown in [30, 31], some parameters among different stages can be shared to reduce the network parameters while maintaining or improving its performance. This paper proposes to recursively utilize LSTM bottleneck in different stages to significantly reduce the number of parameters. While in both encoders and decoders, we do not share the parameters due to that their trainable parameters are much smaller than those of the LSTM module. Skip connection is introduced to compensate for the information loss during the feature compression process and is proved to be helpful for gradient flow. Additionally, different from the dense connection in [22] that current outputs are concatenated with previous outputs in the feature axes, we choose to combine the outputs in the
Table 1: Detailed parameter setup of the proposed architecture. Our proposed model contains multiple stages for progressive noise reduction, where each stage has nearly the same structure except that the input channel of each stage is different. We only show the parameter setup and the tensor size of one stage for compact.

| layer name | input size | hyperparameters | output size |
|------------|------------|-----------------|-------------|
| reshape₁   | $T \times 161$ | -               | $1 \times T \times 161$ |
| cascade₁   | $1 \times T \times 161$ | $q \times T \times 161$ | $q \times T \times 161$ |
| conv2d₁    | $q \times T \times 161$ | $2 \times 3, (1, 2), 16$ | $16 \times T \times 80$ |
| conv2d₂    | $16 \times T \times 80$ | $2 \times 3, (1, 2), 16$ | $16 \times T \times 39$ |
| conv2d₃    | $16 \times T \times 39$ | $2 \times 3, (1, 2), 16$ | $16 \times T \times 19$ |
| conv2d₄    | $16 \times T \times 19$ | $2 \times 3, (1, 2), 32$ | $32 \times T \times 9$ |
| conv2d₅    | $32 \times T \times 9$ | $2 \times 3, (1, 2), 64$ | $64 \times T \times 4$ |
| reshape₂   | $64 \times T \times 4$ | -               | $T \times 256$ |
| lstm₁ (reuse) | $T \times 256$ | $256$ | $T \times 256$ |
| lstm₂ (reuse) | $T \times 256$ | $256$ | $T \times 256$ |
| reshape₃   | $T \times 256$ | -               | $64 \times T \times 4$ |
| deconv2d₁  | $128 \times T \times 4$ | $2 \times 3, (1, 2), 32$ | $32 \times T \times 9$ |
| deconv2d₂  | $64 \times T \times 9$ | $2 \times 3, (1, 2), 16$ | $16 \times T \times 19$ |
| deconv2d₃  | $32 \times T \times 19$ | $2 \times 3, (1, 2), 16$ | $16 \times T \times 39$ |
| deconv2d₄  | $32 \times T \times 39$ | $2 \times 3, (1, 2), 16$ | $16 \times T \times 80$ |
| deconv2d₅  | $32 \times T \times 80$ | $2 \times 3, (1, 2), 1$ | $1 \times T \times 161$ |
| reshape₄   | $1 \times T \times 161$ | -               | $T \times 161$ |

different stages along the channel axes, which could be beneficial for CNN training while effectively decreasing the additional parameters. Note that when IAM serves as the training target, before the current output is sent to the next stage, it needs to be multiplied with the noisy spectrum to obtain the estimated TMS.

A more detailed description of the proposed progressive learning architecture can refer to Table 1. The whole network consists of three cascaded sub-models. As a result, only the sub-model parameter setting is detailed provided in the table. The input size and the output size of 3-D tensor representation are specified with \((Channels \times Timestep \times FrequencyFeat)\) format, while, for 2-D tensor representation, it is specified with \((Timestep \times FrequencyFeat)\). The hyperparameters are specified with \(KernelSize, Stride\) and \(ChannelNumber\) format. For stage \(q\), the number of input channels is set to \(q\) to satisfy the dense connection principle as shown in Table 1.
Table 2: SNR improvement setting of intermediate stages for different $Q$

| Stage number $Q$ | Intermediate SNR improvement |
|------------------|------------------------------|
| 2                | $+20\text{dB}$              |
| 3                | $+10\text{dB, +20dB}$       |
| 4                | $+5\text{dB, +10dB, +20dB}$ |
| 5                | $+5\text{dB, +10dB, +15dB, +20dB}$ |

4. EXPERIMENTS

4.1. Datasets Preparation

Extensive experiments are conducted with the TIMIT corpus, which include 630 speakers of eight major dialects of American English with each reading tens utterances. 2000, 400 and 100 utterances are selected as the training, evaluation and testing datasets, respectively. Training dataset are mixed under different SNR levels ranging from $-5\text{dB}$ to $10\text{dB}$ with the interval 1dB while testing datasets are mixed under $(-5\text{dB}, 0\text{dB}, 5\text{dB}, 10\text{dB})$. 115 types of noises [8, 33] are utilized for training. To explore the generalization capacity of the model, five types of unseen test noises from NOISEX92 [34] are utilized, including babble, f16, factory2, m109 and white.

Various noises are first concatenated into a long vector. During the mixing process, the random cutting point is selected to obtain the noise-only signal, which is subsequently mixed with a clean utterance under one random chosen SNR condition. As a result, a total of 20,000, 2,000 and 800 contaminated utterances and their clean version pairs are built for training, evaluation and testing, respectively. Table 2 summarizes multiple intermediate targets with different SNR improvement levels over the originally noisy utterance.

The feature extraction approach takes as follows. For the sampling rate 16 kHz, the 20-ms Hamming window function is applied with 10-ms overlap. A 320-point STFT is adopted, leading to a 161-D feature vector for each frame. Instead of using the logarithm power spectrum (LPS), we use the magnitude as the feature directly, which is the same as [23] for fair comparisons. Besides,
we use the same values of $\alpha_q$ as \cite{21}, where $\alpha_q = 0.1$ for $q = 1, \cdots, Q - 1$ and $\alpha_Q = 1$.

### 4.2. Comparison Models

In our experiments, we compare our proposed model with another four baselines, i.e., progressive learning with feedforward DNN \cite{21}, LSTM-based progressive learning with dense connection \cite{22}, autoencoder-based CRNN in real-time \cite{23} and its simplified version with smaller training parameters, which are termed as PL-DNN, PL-LSTM, CRNN, and SCRNN, respectively. Follow the literature \cite{22}, $Q = 3$ is chosen to compare previous PL-based networks with the proposed PL-CRNN. In addition, PL-CRNN with $Q = 5$ is also presented to compare with the latter two baselines, i.e., CRNN and SCRNN. All the models are configured as the causal models, given as follows:

1. **PL-DNN.** Slightly different from the literature \cite{21}, we take the causal strategy for a fair comparison and the previous 10 frames are combined together with the current frame to form a larger feature vector, i.e., $161 \times 11 = 1771$. As a consequence, the structure of PL-DNN is $\{2048 - 2048 - 161 - 2048 - 2048 - 161 - 2048 - 161\}$.

2. **PL-LSTM.** The structure of PL-LSTM is $\{1024 - 1024 - 161 - 1024 - 1024 - 161 - 1024 - 1024 - 161\}$, where 1024 refers to LSTM layer and 161 is the affine layer. In addition, dense connection is utilized in adjacent stages and post-processing (PP) is applied to both PL-DNN and PL-LSTM by averaging the outputs in different stages, which have been proved to further improve its performance \cite{22}.

3. **CRNN.** It has a similar structure with the proposed sub-net but with much more trainable parameters, which is known as one of the state-of-the-art models. The output channels of the encoder are 256 and the number of LSTM units is 1024.

4. **SCRNN.** Compared with CRNN, it decreases the number of parameters for both CNN and LSTM modules. That is to say, it has about a quarter of
the trainable parameters compared with CRNN. SCRNN is presented here to show the performance degradation when simply reducing the number of parameters of CRNN.

4.3. Optimization Details

All the models are trained with Adam optimizer [35]. The learning rate is initialized at 0.001. We halve the learning rate only when consecutive 3 evaluation loss increment arises and the training process is early-stopped only if more than 10 increment on evaluation loss happens. We train the model for 100 epochs to guarantee the model convergence. The minibatch is set to 16 at a utterance level. Within a minibatch, zero value is padded for all the utterances whose timestep length is less than the longest one. For PL-DNN, utterances from a minibatch are reshaped into \((\text{Batch} \times \text{Timestep} \times \text{FrequencyFeat})\) format to meet the required input size.

5. RESULTS AND ANALYSIS

5.1. Evaluation Metrics

In this study, we evaluate the performance of different models in terms of speech quality and speech intelligibility with three objective metrics, containing perceptual evaluation of speech quality (PESQ) [36], short-time objective intelligibility (STOI) [37] and source-to-distortion ratio (SDR) [38].

5.2. the Influence of Multi-stage

We first demonstrate the influence of multi-stage from the perspective of the number of stages \(Q\). As stated before, the previous stages can boost performance in the subsequent task. Generally, when the number of stages increases, it is expected to improve the performance. Therefore, we train the network PL-CRNN with a smaller training dataset under different number of stages to study its influence on speech enhancement. The training set consists of 10,000 noisy-clean pairs that are randomly selected from the original training dataset. TMS
is the training target. The testing results are averaged under both seen and unseen noise conditions, which are presented in Fig. 4. The results of CRNN are also given for comparison.

From Fig. 4, one can observe that both metrics achieve an overall improvement with the increase of the number of stages. Specifically, when $Q = 4$, PL-CRNN has better performance than CRNN in terms of both PESQ and STOI. Additionally, as parameter-efficient encoder and decoder are utilized for each stage, the increase of the number of stages will introduce only limited extra parameters. However, for PL-DNN and PL-LSTM, the increase of the number of stages will introduce inefficient FC and LSTM layers.

5.3. Objective Results Comparison

Table 3 and Table 4 summarize the results of different models for seen and unseen cases, respectively. Two targets (TMS and IAM) are studied for both baselines and the proposed architecture. $Q = 3$ is chosen if not specially noted for PL-based models.

5.3.1. Comparison with previous PL-based models

We first compare the results among PL-based models with the same number of stages. From the tables, one can have the following findings. (1) Both PL-
DNN and PL-LSTM can effectively improve speech quality and intelligibility for both seen and unseen noise, which is consistent with the results in [21][22]. (2) compared with PL-DNN, PL-LSTM achieves relatively better performance in terms of all the three metrics, which can be explained from three perspectives. One is that the LSTM layer is capable of utilizing sequence dependencies from previous timesteps while the DNN layer only captures contextual information with a preset frame window, which heavily limits the performance. Another is that dense operation along the frequency axes is helpful to aggregate the information from the previous stages. The other is that ReLU is helpful for gradient flow when exploring a depth network compared with the sigmoid function. (3) A notable improvement in three metrics is observed for PL-CRNN compared with the baselines. For example, when going from PL-LSTM to PL-CRNN, an average PESQ improvement of 0.18 is observed for unseen case while about 0.12 improvement for unseen case. The reasons behind the results can be explained as higher efficiency can be achieved when the sub-net in each stage is CRNN instead of simple FC or LSTM layers. On one hand, convolutional auto-encoder is applied, which facilitates the spectral patterns to be better explored and learned during the training. On the other hand, recursive LSTM layers are applied as the sequence modeling part, which can effectively model the sequence correlation in different stages while dramatically decreasing the trainable parameters. Besides, the usage of dense connection along channel axes introduces negligibly extra parameters compared with dense connection along feature axes.

5.3.2. Comparison with CRNNs

In this section, we compare the performance between CRNNs and PL-CRNN with $Q = 5$. The following phenomena can be observed. (1) PL-CRNN obtains the overall superiority compared with CRNN but with much fewer parameters, which will be further analyzed in the next part. For example, going from CRNN to PL-CRNN, an average PESQ improvement is about 0.04, which proves the effectiveness of PL-CRNN with the increase of the number of stages. There are two main reasons. First, the use of progressive learning is helpful to compensate
Table 3: Experimental results with seen noise under different SNR conditions among PL-based models. **BOLD** indicates the best result for each case. Average values are also given for better comparison. TMS and IAM are two targets in this study. The number of stages is \( Q = 3 \) for all PL-based algorithm if no emphasis is given.

| Metrics | PESQ | STOI (in %) | SDR (in dB) |
|---------|------|-------------|-------------|
| **SNR (dB)** | -5 | 0 | 5 | Avg. | -5 | 0 | 5 | 10 | Avg. | -5 | 0 | 5 | 10 | Avg. |
| Noisy | 1.43 | 1.77 | 2.16 | 2.48 | 1.96 | 62.24 | 72.22 | 81.29 | 88.82 | 76.15 | 1.59 | 0.20 | 5.18 | 10.07 | 2.69 |
| **TMS** | | | | | | | | | | | | | | | |
| PL-DNN | 1.88 | 2.38 | 2.70 | 2.98 | 2.49 | 74.54 | 83.46 | 90.02 | 92.75 | 84.94 | 7.47 | 9.29 | 12.61 | 15.15 | 10.58 |
| PL-LSTM | 2.08 | 2.47 | 2.79 | 3.08 | 2.60 | 75.25 | 85.07 | 90.44 | 94.09 | 86.46 | 5.90 | 9.52 | 11.11 | 16.24 | 11.19 |
| PL-CRNN | 2.28 | 2.64 | 2.96 | 3.21 | 2.77 | 78.57 | 86.80 | 91.61 | 94.92 | 87.99 | 7.77 | 10.75 | 14.29 | 17.39 | 12.55 |
| CRNN | 2.29 | 2.67 | 2.98 | 3.25 | 2.80 | 78.47 | 86.71 | 91.68 | 94.89 | 87.84 | 7.71 | 10.76 | 14.29 | 17.42 | 12.54 |
| SCRNN | 2.20 | 2.59 | 2.91 | 3.18 | 2.72 | 77.25 | 85.97 | 90.88 | 94.21 | 87.08 | 7.22 | 9.97 | 13.65 | 16.80 | 11.91 |
| PL-CRNN (Q = 5) | \(2.36\) | \(2.71\) | \(3.00\) | \(3.25\) | \(2.83\) | \(79.60\) | \(87.43\) | \(92.08\) | \(95.21\) | \(88.58\) | \(8.14\) | \(11.24\) | \(14.50\) | \(17.63\) | \(12.88\) |
| **IAM** | | | | | | | | | | | | | | | |
| PL-DNN | 2.00 | 2.38 | 2.70 | 2.99 | 2.32 | 74.30 | 83.17 | 88.12 | 91.29 | 84.97 | 7.39 | 9.19 | 12.96 | 16.34 | 10.97 |
| PL-LSTM | 2.09 | 2.46 | 2.79 | 3.07 | 2.60 | 75.62 | 84.60 | 90.14 | 94.15 | 86.13 | 5.81 | 9.52 | 13.15 | 16.83 | 11.38 |
| PL-CRNN | 2.31 | 2.67 | 2.98 | 3.24 | 2.80 | 78.50 | 86.63 | 91.49 | 94.74 | 87.84 | 7.84 | 10.83 | 14.38 | 17.47 | 12.63 |
| CRNN | 2.32 | 2.67 | 2.99 | 3.23 | 2.84 | 78.71 | 86.64 | 91.46 | 94.81 | 87.80 | 7.88 | 10.84 | 14.39 | 17.48 | 12.65 |
| SCRNN | 2.25 | 2.61 | 2.93 | 3.20 | 2.75 | 77.12 | 85.64 | 90.57 | 94.06 | 86.85 | 7.32 | 10.31 | 13.87 | 17.01 | 12.13 |
| PL-CRNN (Q = 5) | \(2.38\) | \(2.72\) | \(3.01\) | \(3.26\) | \(2.84\) | \(79.35\) | \(87.21\) | \(91.69\) | \(94.99\) | \(88.31\) | \(8.00\) | \(11.28\) | \(14.58\) | \(17.65\) | \(12.88\) |

Second, the intermediate mapping results actually serve as the prior information to boost the subsequent mapping process. (2) SCRNN has the same architecture as CRNN except that the number of parameters is reduced to 25%. One can get that SCRNN decreases PESQ by average 0.07 and STOI by 0.95% compared with CRNN for seen noise. This result confirms that the performance of CRNN may reduce its performance with less parameters.

Speech spectrograms are presented in Fig 5. It is obvious that, compared with PL-DNN and PL-LSTM, both CRNN and PL-CRNN can better reconstruct the spectral details of the speech signal while both of them can effectively remove the non-stationary noise components.

5.4. Model Comparison

To compare the above mentioned models, we introduce the principle of calculation in terms of floating-point fused multiply-adds (FMAs) for different networks [39]. Note that FMAs of BN and nonlinear activation functions are few so that they are often neglected during evaluating the computational complexity.

As convolutional layer and fully-connected layer are two most common layers in neural network, their calculation formulas are given in the Table 5 where...
Figure 5: Speech spectrograms obtained using different models under 0dB with the unseen factory2 noise. The utterance is selected from the testing dataset and TMS is the training target. (a) Noisy utterance, PESQ = 1.85, STOI = 0.76. (b) Clean utterance, PESQ = 4.50, STOI = 1.00. (c) PL-DNN, PESQ = 2.36, STOI = 0.87. (d) PL-LSTM, PESQ = 2.44, STOI = 0.88. (e) CRNN, PESQ = 2.55, STOI = 0.89. (f) PL-CRNN1, PESQ = 2.60, STOI = 0.90.
Table 4: Experimental results with unseen noise under different SNR conditions among PL-based models. **BOLD** indicates the best result for each case. Average values are also given for better comparison. TMS and IAM are two targets in this study. The number of stages is $Q = 3$ for all PL-based models if no emphasis is given.

| Metrics | PESQ | STOI (in %) | SDR (in dB) | SNR (dB) |
|---------|------|-------------|-------------|--------|
| SNR (dB) | -5 | 0 | 5 | 10 | Avg. | -5 | 0 | 5 | 10 | Avg. | -5 | 0 | 5 | 10 | Avg. |
| Noisy   | 1.49 | 1.86 | 2.19 | 2.49 | 1.99 | 59.67 | 71.22 | 81.45 | 89.24 | 75.40 | 4.80 | 0.16 | 5.07 | 10.06 | 2.61 |
| TMS     | PL-DNN | 1.84 | 2.26 | 2.63 | 2.90 | 2.41 | 68.63 | 79.98 | 87.41 | 92.00 | 82.00 | 1.10 | 7.86 | 11.78 | 14.82 | 9.30 |
|         | PL-LSTM | 1.96 | 2.38 | 2.74 | 3.00 | 2.52 | 71.48 | 82.34 | 89.32 | 93.20 | 84.08 | 1.92 | 8.54 | 12.20 | 15.79 | 10.11 |
|         | CRNN | 2.07 | 2.51 | 2.87 | 3.13 | 2.65 | 72.51 | 83.42 | 90.89 | 94.09 | 85.03 | 5.10 | 9.44 | 12.98 | 16.78 | 11.07 |
|         | SCRNN | 2.02 | 2.45 | 2.82 | 3.08 | 2.79 | 72.24 | 82.94 | 89.36 | 93.38 | 84.48 | 4.86 | 9.06 | 12.48 | 16.22 | 10.65 |
|         | PL-CRNN (Q = 5) | 2.13 | 2.55 | 2.90 | 3.16 | 2.69 | 73.58 | 84.10 | 90.52 | 94.44 | 85.66 | 5.62 | 9.83 | 13.30 | 16.99 | 11.43 |
| IAM     | PL-DNN | 1.81 | 2.24 | 2.62 | 2.88 | 2.39 | 67.69 | 79.96 | 87.29 | 92.38 | 81.68 | 3.00 | 7.76 | 11.78 | 15.79 | 9.58 |
|         | PL-LSTM | 1.94 | 2.35 | 2.72 | 2.99 | 2.50 | 70.20 | 81.19 | 88.68 | 93.14 | 83.15 | 3.64 | 7.75 | 12.18 | 16.12 | 10.05 |
|         | CRNN | 2.05 | 2.51 | 2.87 | 3.15 | 2.64 | 72.15 | 83.34 | 90.71 | 94.88 | 85.77 | 5.28 | 9.55 | 12.18 | 16.12 | 11.18 |
|         | SCRNN | 2.07 | 2.51 | 2.88 | 3.16 | 2.65 | 72.80 | 83.27 | 89.76 | 93.88 | 84.93 | 5.25 | 9.51 | 13.00 | 16.76 | 11.13 |
|         | PL-CRNN | 2.12 | 2.55 | 2.90 | 3.16 | 2.69 | 72.59 | 83.54 | 89.89 | 94.03 | 85.02 | 5.68 | 9.85 | 13.23 | 16.95 | 11.43 |

Table 5: Calculation formulas of FMA for convolutional layer and fully-connected layer.

| Unit                              | Formula                                      |
|-----------------------------------|----------------------------------------------|
| Convolutional layer (Conv)        | $O\left( T \cdot F_{i} \cdot K_{T} \cdot K_{F} + 1 \right) \cdot C_{out}$ |
| Fully-connected layer (FC)        | $O\left( F_{i} \cdot F_{o} \right)$         |

$T$ and $F$ denote the size of output feature map in time dimension and that in feature dimensions, respectively. $C_{in}$ and $C_{out}$ denote the number of channels for the input and the output feature maps, respectively. $K$ refers to the kernel size. Note that +1 indicates the bias is also considered. $F_{i}$ and $F_{o}$ are respectively the number of input neurons and that of output neurons. RNN unit is not considered separately as it can be essentially viewed as a type of FC operation with recurrent connection. Accordingly, FMAs can be given by:

$$O = \sum_{i=1}^{I} \{O(\text{Conv}_i), O(\text{FC}_i)\},$$

(5)

where $I$ refers to the layer set.

The number of parameters and FMAs for different architectures are given in Table 6. As Table 6 shows, compared with the baselines, PL-CRNN has the smallest number of trainable parameters, which indicates the highest parameter efficiency of PL-CRNN. In addition, We notice that PL-CRNN has slightly more FMAs than SCRNN when $Q = 5$. This is because FMAs has a linear...
Table 6: The number of trainable parameters (NumOfParas) and FMAs. **Bold** indicates the smallest value is achieved for each case. The number of stages is $Q = 3$ for all PL-based models if no emphasis is given. The unit is million.

| Models            | NumOfParas | FMAs |
|-------------------|------------|------|
| PL-DNN            | 17.87      | 17.87|
| PL-LSTM           | 42.25      | 42.25|
| CRNN              | 17.59      | 25.28|
| SCRNN             | 4.40       | 6.34 |
| PL-CRNN           | **1.22**   | **5.96**|
| PL-CRNN (Q=5)     | 1.33       | 9.94 |

relationship with the number of stages $Q$, which can be dramatically decreased by reducing $Q$. However, note that PL-CRNN with $Q = 3$ has the smaller FMAs than SCRNN and its performance is still better. Besides we observe that a larger number of parameters with multiple-stacked LSTM layers do not bring obvious performance improvement, which explains the saturation effect of LSTM-only network [22, 23].

6. Conclusions

In this paper, we propose a progressive learning framework for CRNN, which takes advantage of both CNN and RNN to significantly reduce the number of parameters when compared with PL-DNN, PL-LSTM, and CRNN. Experimental results show that the proposed PL-CRNN algorithm obtains consistently better performance than the competing algorithms in terms of PESQ, STOI, and SDR.

References

References

[1] P. C. Loizou, Speech enhancement: theory and practice, CRC press, 2013.

[2] S. Boll, Suppression of acoustic noise in speech using spectral subtraction, IEEE Transactions on acoustics, speech, and signal processing, 27(2) (1979) 113–120.
[3] H. Hu, S. Wang, C. Zheng, X. Li, A cepstrum-based preprocessing and postprocessing for speech enhancement in adverse environments, Applied Acoustics. 74(12) (2013) 1458–1462.

[4] J. Chen, J. Benesty, Y. Huang, S. Doclo, New insights into the noise reduction wiener filter, IEEE Transactions on audio, speech, and language processing. 14(4) (2006) 1218–1234.

[5] C. Zheng, R. Peng, X. Li, A Constrained MMSE LP Residual Estimator for Speech Dereverberation in Noisy Environments, IEEE Signal Processing Letters. 21(12) (2014) 1462–1466.

[6] S. H. Jensen, P. C. Hansen, S. D. Hansen, J. A. Sorensen, Reduction of broad-band noise in speech by truncated qsvd, IEEE Transactions on Speech and Audio Processing. 3(6) (1995) 439–448.

[7] E. W. Healy, S. E. Yoho, Y. Wang, D. Wang, An algorithm to improve speech recognition in noise for hearing-impaired listeners, The Journal of the Acoustical Society of America. 134(4) (2013) 3029–3038.

[8] Y. Xu, J. Du, L.-R. Dai, C.-H. Lee, A regression approach to speech enhancement based on deep neural networks, IEEE/ACM Transactions on Audio, Speech, and Language Processing. 23(1) (2014) 7–19.

[9] Y. Xu, J. Du, L.-R. Dai, C.-H. Lee, Global variance equalization for improving deep neural network based speech enhancement, in: 2014 IEEE China Summit & International Conference on Signal and Information Processing (ChinaSIP), IEEE, 2014, pp. 71–75.

[10] S.-W. Fu, T.-y. Hu, Y. Tsao, X. Lu, Complex spectrogram enhancement by convolutional neural network with multi-metrics learning, in: 2017 IEEE 27th International Workshop on Machine Learning for Signal Processing (MLSP), IEEE, 2017, pp. 1–6.
[11] D. Wang, J. Chen, Supervised speech separation based on deep learning: An overview, IEEE/ACM Transactions on Audio, Speech, and Language Processing. 26(10) (2018) 1702–1726.

[12] D. S. Williamson, Y. Wang, D. Wang, Complex ratio masking for monaural speech separation, IEEE/ACM Transactions on Audio, Speech and Language Processing (TASLP). 24(3) (2016) 483–492.

[13] Y. Wang, A. Narayanan, D. Wang, On training targets for supervised speech separation, IEEE/ACM Transactions on Audio, Speech, and Language Processing. 22(12) (2014) 1849–1858.

[14] D. Wang, On ideal binary mask as the computational goal of auditory scene analysis, in: Speech separation by humans and machines, Springer, 2005, pp. 181–197.

[15] C. Hummersone, T. Stokes, T. Brookes, On the ideal ratio mask as the goal of computational auditory scene analysis, in: Blind source separation, Springer, 2014, pp. 349–368.

[16] S. R. Park, J. W. Lee, A fully convolutional neural network for speech enhancement, Proc. Interspeech 2017 (2017) 1993–1997.

[17] S.-W. Fu, Y. Tsao, X. Lu, SNR-aware convolutional neural network modeling for speech enhancement., in: Interspeech, 2016, pp. 3768–3772.

[18] F. Weninger, H. Erdogan, S. Watanabe, E. Vincent, J. Le Roux, J. R. Hershey, B. Schuller, Speech enhancement with lstm recurrent neural networks and its application to noise-robust asr, in: International Conference on Latent Variable Analysis and Signal Separation, Springer, 2015, pp. 91–99.

[19] J. Chen, D. Wang, Long short-term memory for speaker generalization in supervised speech separation, The Journal of the Acoustical Society of America. 141(6) (2017) 4705–4714.
[20] H. Zhao, S. Zarar, I. Tashev, C.-H. Lee, Convolutional-recurrent neural networks for speech enhancement, in: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, 2018, pp. 2401–2405.

[21] T. Gao, J. Du, L.-R. Dai, C.-H. Lee, SNR-based progressive learning of deep neural network for speech enhancement, in: INTERSPEECH, 2016, pp. 3713–3717.

[22] T. Gao, J. Du, L.-R. Dai, C.-H. Lee, Densely connected progressive learning for LSTM-based speech enhancement, in: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, 2018, pp. 5054–5058.

[23] K. Tan, J. Chen, D. Wang, Gated residual networks with dilated convolutions for monaural speech enhancement, IEEE/ACM Transactions on Audio, Speech, and Language Processing. 27(1) (2018) 189–198.

[24] K. Tan, D. Wang, A convolutional recurrent neural network for real-time speech enhancement., in: Interspeech, 2018, pp. 3229–3233.

[25] F. Weninger, J. R. Hershey, J. Le Roux, B. Schuller, Discriminatively trained recurrent neural networks for single-channel speech separation, in: 2014 IEEE Global Conference on Signal and Information Processing (GlobalSIP), IEEE, 2014, pp. 577–581.

[26] A. van den Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. Senior, K. Kavukcuoglu, Wavenet: A generative model for raw audio, in: 9th ISCA Speech Synthesis Workshop, pp. 125–125.

[27] S. Ioffe, C. Szegedy, Batch normalization: Accelerating deep network training by reducing internal covariate shift, in: International Conference on Machine Learning, 2015, pp. 448–456.
[28] D.-A. Clevert, T. Unterthiner, S. Hochreiter, Fast and accurate deep network learning by exponential linear units (elus), arXiv preprint arXiv:1511.07289.

[29] H. Noh, S. Hong, B. Han, Learning deconvolution network for semantic segmentation, in: Proceedings of the IEEE international conference on computer vision, 2015, pp. 1520–1528.

[30] J. Kim, J. Kwon Lee, K. Mu Lee, Deeply-recursive convolutional network for image super-resolution, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 1637–1645.

[31] D. Ren, W. Zuo, Q. Hu, P. Zhu, D. Meng, Progressive image deraining networks: a better and simpler baseline, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 3937–3946.

[32] H. Zheng, Z. Yang, W. Liu, J. Liang, Y. Li, Improving deep neural networks using softplus units, in: 2015 International Joint Conference on Neural Networks (IJCNN), IEEE, 2015, pp. 1–4.

[33] G. Hu, D. Wang, A tandem algorithm for pitch estimation and voiced speech segregation, IEEE Transactions on Audio, Speech, and Language Processing. 18(8) (2010) 2067–2079.

[34] A. Varga, H. J. Steeneken, Assessment for automatic speech recognition: Ii. noisex-92: A database and an experiment to study the effect of additive noise on speech recognition systems, Speech communication. 12(3) (1993) 247–251.

[35] D. P. Kingma, J. Ba, Adam: A method for stochastic optimization, arXiv preprint arXiv:1412.6980.

[36] A. W. Rix, J. G. Beerends, M. P. Hollier, A. P. Hekstra, Perceptual evaluation of speech quality (pesq)-a new method for speech quality assessment
of telephone networks and codecs, in: 2001 IEEE International Conference on Acoustics, Speech, and Signal Processing. Proceedings (Cat. No. 01CH37221), Vol. 2, IEEE, 2001, pp. 749–752.

[37] C. H. Taal, R. C. Hendriks, R. Heusdens, J. Jensen, An algorithm for intelligibility prediction of time–frequency weighted noisy speech, IEEE Transactions on Audio, Speech, and Language Processing. 19(7) (2011) 2125–2136.

[38] E. Vincent, R. Gribonval, C. Févotte, Performance measurement in blind audio source separation, IEEE transactions on audio, speech, and language processing. 14(4) (2006) 1462–1469.

[39] H. Li, A. Kadav, I. Durdanovic, H. Samet, and H. P. Graf, Pruning filters for efficient convnets, in: ICLR, 2017.