A Time-domain Monaural Speech Enhancement with Recursive Learning

Andong Li\textsuperscript{1,2}, Chengshi Zheng\textsuperscript{1,2}, Linjuan Cheng\textsuperscript{1,2}, Renhua Peng\textsuperscript{1,2}, Xiaodong Li\textsuperscript{1,2}

\textsuperscript{1} Key Laboratory of Noise and Vibration Research, Institute of Acoustics, Chinese Academy of Sciences, Beijing, China
\textsuperscript{2}University of Chinese Academy of Sciences, Beijing, China

\{liandong, cszheng, chenglinjuan, pengrenhua, lx\}@mail.ioa.ac.cn

Abstract

In this paper, we propose a type of neural network with recursive learning in the time domain called RTNet for monaural speech enhancement, where the proposed network consists of three principal components. The first part is called stage recurrent neural network, which is introduced to effectively aggregate the deep feature dependencies across different stages with a memory mechanism and also remove the interference stage by stage. The second part is the convolutional auto-encoder. The third part consists of a series of concatenated gated linear units, which are capable of facilitating the information flow and gradually increasing the receptive fields. Recursive learning is adopted to improve the parameter efficiency and therefore, the number of trainable parameters is effectively reduced without sacrificing its performance. Numerous experiments are conducted on TIMIT corpus and experimental results demonstrate that the proposed network can achieve consistently better performance in terms of both PESQ and STOI scores than two state-of-the-art time-domain-based baselines in different conditions. The code is provided at https://github.com/Andong-Li-speech/RTNet.

Index Terms: noise reduction, recursive learning, time domain, convolutional network

1. Introduction

Speech is often inevitably degraded by background interference in real environments, which may significantly reduce the performance of automatic speech recognition (ASR), speech communication system and hearing aids. Monaural speech enhancement is dedicated to effectively extracting underlying target speech from its degraded version when only one measurement is available\cite{1}. There are many well-known signal-processing-based approaches, such as spectral subtraction \cite{2}, Wiener filtering \cite{3} and statistical-based methods \cite{4}.

Recent advances in deep neural networks (DNNs) have facilitated the rapid development of speech enhancement research, and a great diversity of DNN models have been proposed to tackle the nonlinear mapping problem from the noisy speech to the clean speech (see \cite{5, 6} and references therein). A typical DNN-based speech enhancement framework extracts temporal-frequency (T-F) features of the noisy speech and calculates some T-F representation targets of the clean speech. A model is then trained to establish the complicated mapping from the input features to the output targets with some supervised methods. Training targets can be categorized into two types, where one is the masking-based \cite{7} and the other one is the spectral mapping-based \cite{6, 8}.

Although the approaches based on the T-F domain are remarkable \cite{6, 7, 8}, they still have several limitations. Firstly, when the pre-processing and post-processing operations are applied using short-time Fourier transform (STFT) and inverse short-time Fourier transform (iSTFT), the signal delay is inevitable due to employing a uniform and fixed analysis-synthesis filterbank. As shown in \cite{9}, STFT can be replaced by a type of one-dimensional convolutional (1-D Conv) operation with fixed coefficients, and better performance is observed when they are adaptively learned from the training data. Secondly, conventional DNNs often only estimate the spectral magnitude of the speech, and then incorporate with the noisy phase to reconstruct the enhanced speech, which may restrict the upper performance and cause some artifacts under low SNR conditions as phase is not optimized \cite{10}. Some networks considering phase recovery are proposed \cite{11, 12}. Moreover, STFT inconsistency and the mixture inconsistency may arise for many T-F domain-based networks \cite{13, 14}, i.e., no corresponding time-domain signal is guaranteed to exist for enhanced speech spectrogram.

For the above reasons, a variety of time-domain-based networks have been proposed recently \cite{15, 16, 17, 18}. Similar to T-F domain-based networks, these processing systems also require a large number of trainable parameters, which may increase the computational complexity for practical applications. More recently, progressive learning (PL) has been applied in various tasks like single image deraining \cite{19} and speech enhancement \cite{20}, where the whole mapping procedure is decomposed into multiple stages. In our preliminary work, we propose a PL-based convolutional recurrent network (PL-CRN) \cite{21}, where the noise components are gradually attenuated with a light-weight convolutional recurrent network (CRN) in each stage. We attribute the success of PL to the accumulation of prior information with the increase of the stages, i.e., all the outputs in the previous stages actually serve as the prior information to facilitate the execution of subsequent stages. Motivated by this, we propose a novel time-domain-based network with a recursive mechanism called RTNet, which needs much fewer trainable parameters. It works by recursively incorporating the estimated output from the last stage along with the original noisy feature back to the network, where each temporary output can be regarded as a type of state among different stages , and then trained with a recurrent approach. By doing so, the feature dependencies across different stages can be fully exploited and the output estimation can be refined stage by stage.

The remainder of this paper is structured as follows. Section 2 formulates the problem and briefly introduces SRN and GLU. The proposed architecture is described in Section 3. Section 4 presents the experimental settings. Experimental results and analysis are given in Section 5. Some conclusions are made in Section 6.

2. Network module

In the time domain, a mixture signal is usually formulated as $x(k) = s(k) + d(k)$, where $k$ denotes the time index, $s(k)$,
\[ d(k), \text{ and } x(k) \text{ are the clean speech, the noise, and the noisy speech, respectively. The network aims to estimate the time-domain clean speech. The proposed architecture is in essence a type of multi-stage network, where the estimated output from the last stage combined with the original noisy input is sent back to the network. For notation convenience, we denote the frame vector of the noisy signal, estimation in its stage, and the final output in the time domain as } x \in \mathbb{R}^K, \hat{s}^l \in \mathbb{R}^K, \hat{s} \in \mathbb{R}^K, \text{ respectively, where } K \text{ is the frame length. The number of the stages is denoted as } Q. \text{ For the } l^{th} \text{ stage, the mapping process can be formulated as: } \\
\hat{s}^l = g_{\theta}(x, \hat{s}^{l-1}), \quad (1) \]

where \( g_{\theta}(.) \) represents the network function.

### 2.1. Stage recurrent neural network

In this study, we explore the time dependencies of different stages and a type of recurrent convolutional structure named stage recurrent neural network (SRNN) is proposed. Theoretically, the learning process from the noisy feature to the clean target can be viewed as a type of sequence learning, where each state represents the intermediate output in one stage. As a consequence, the network can be trained following a recurrent learning paradigm. As shown in Fig. 1, SRNN contains two parts, namely 1-D Conv block and convolutional-RNN (ConvRNN). Assuming the inputs are \( x \) and \( \hat{s}^{l-1} \), and the output of the 1-D Conv block is denoted as \( \hat{h}^l \). Then \( \hat{h}^l \) along with the hidden state vector from the last stage \( \hat{h}^{l-1} \) is sent to ConvRNN to obtain a updated hidden state, i.e., \( \hat{h}^l \). As a result, the inference of \( h^l \) can be formulated as

\[ \hat{h}^l = f_{\text{conv}}(x, \hat{s}^{l-1}), \quad (2) \]
\[ h^l = f_{\text{conv}, \text{rnn}}(\hat{h}^l, \hat{h}^{l-1}), \quad (3) \]

where \( f_{\text{conv}}(.) \) and \( f_{\text{conv}, \text{rnn}}(.) \) represent the functions of 1-D Conv block and ConvRNN block, respectively.

In this study, ConvGRU [22] is adopted as the unit for Conv-RNN, given as follows:

\[ z^l = \sigma \left( W^z_l \odot \hat{h}^l + U^z_l \odot h^{l-1} \right), \quad (4) \]
\[ r^l = \sigma \left( W^r_l \odot \hat{h}^l + U^r_l \odot h^{l-1} \right), \quad (5) \]
\[ n^l = \tanh \left( W^n_l \odot \hat{h}^l + U^n_l \odot \left( r^l \odot h^{l-1} \right) \right), \quad (6) \]
\[ h^l = \left( 1 - z^l \right) \odot \hat{h}^l + z^l \odot n^l, \quad (7) \]

where \( \sigma(\cdot) \) and \( \tanh(\cdot) \), respectively, denote the sigmoid and the tanh activation functions. \( W \) and \( U \) refer to the weight matrices of the cell. \( \odot \) represents the convolutional operator and \( \odot \) is the element-wise multiplication. Note that all the biases are neglected for notation simplicity.

#### 2.2. Gated linear unit

Gated convolutional layer is first introduced in [23] to model complicated interactions in the form of a gating mechanism which is beneficial to performance and its modified version
channel axis to execute the next recursive stage. Here we only impose supervision on the final output \( \tilde{s} \), which is consistent with the setting in [19].

A more detailed parameter configuration of the proposed network is summarized in Table 1, where the input and output sizes of 2-D tensor representation are specified with \((Channels \times Framesize)\) format. The hyperparameters of the layers except GLUs are specified with \((KernelSize, Strided, Channels)\) format. The hyperparameters of GLUs are specified with \((KernelSize, DilatedRate, Channels)\) format. Bold numbers refer to the dilated rate.

4. Experiments

4.1. Datasets

Experiments are conducted on TIMIT corpus [29], which includes 630 speakers of eight major dialects of American English with each reading ten utterances. 1000, 200 and 100 clean utterances are randomly selected for training, validation and testing, respectively. Training and validation dataset are mixed under SNR levels ranging from -5dB to 10dB with the interval 1dB while the testing datasets are mixed under -5dB and -2dB conditions. During training and validation, we use 130 types of noises, including 115 types used in [21], 9 types from [30], 3 types from NOISEX92 [31] and 3 common environmental noise, i.e. aircraft, bus and cafeteria. Another 5 types of noises from NOISEX92, including bubble, 256, factory2, m109 and white, are chosen to test the network generalization capacity.

Various noises are first concatenated into a long vector. During each mixed process, the cutting point is randomly generated, which is subsequently mixed with a clean utterance under one SNR condition. As a result, totally 10,000, 2000 and 400 noisy-clean utterance pairs are created for training, validation, and testing, respectively.

4.2. Baselines

In this study, two advanced time-domain-based networks are selected as the baselines, namely AECNN [17] and RHR-Net [18]. AECNN is a typical 1-D Conv-based auto-encoder architecture with a large number of trainable parameters. The number of channels in consecutive layers are \{64, 64, 128, 128, 128, 256, 256, 256, 256, 256, 256, 256, 128, 128, 128, 1\}, with 11 and PReLU being the filter size and activation nonlinearity, respectively. RHR-Net has also the form of auto-encoder framework except all the convolutional layers are replaced by bidirectional GRU (BiGRU). In addition, direct skip connections are replaced by PReLU-based residual connections. It achieves state-of-the-art metric performance among several advanced speech enhancement models with limited trainable parameters (see [18]). The number of units per layer are \{1, 32, 64, 128, 256, 128, 64, 32, 1\} and three residual skip connections are introduced. Note that the last layer is a single-directional GRU to produce the enhanced signal.

4.3. Experimental settings

We sample all the utterances at 16kHz. Each frame has a size of 2048 samples (128 ms) with 256 samples (16 ms) offset between adjacent frames. All the models are trained with mean absolute error (MAE) criterion, optimized by Adam algorithm [32]. The learning rate is initialized at 0.0002. We halve the learning rate only if consecutive three validation loss increment arises and the training process is early-stopped only if ten validation loss increment happens. We train all the models for 50 epochs. Within each epoch, the minibatch is set to 2 at the utterance level, where all the utterances are randomly chunked.

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**Table 2:** Experimental results under seen noise conditions for PESQ and STOI. **BOLD** indicates the best result for each case. The number of stages \( Q \) are set to 3, 4 and 5 for model comparisons.

| Metrics | SNR | -5dB | -2dB | Avg. | -5dB | -2dB | Avg. |
|---------|-----|------|------|------|------|------|------|
| PESQ    |     |      |      |      |      |      |      |
| Noisy   | 1.47| 1.47 | 1.57 | 63.03| 68.20| 65.62|
| AECNN   | 2.25| 2.29 | 2.37 | 82.70| 87.51| 85.11|
| RHR-Net | 2.32| 2.55 | 2.44 | 83.13| 87.90| 85.51|
| RTNet (Q = 3) | 2.36| 2.59 | 2.48 | 83.18| 87.92| 85.55|
| RTNet (Q = 4) | 2.35| 2.59 | 2.47 | 83.75| 88.39| 86.07|
| RTNet (Q = 5) | 2.37| 2.60 | 2.48 | 84.03| 88.54| 86.28|

**Table 3:** Experimental results under unseen noise conditions for PESQ and STOI. **BOLD** indicates the best result for each case. The number of stages \( Q \) are set to 3, 4 and 5 for model comparisons.

| Metrics | SNR | -5dB | -2dB | Avg. | -5dB | -2dB | Avg. |
|---------|-----|------|------|------|------|------|------|
| PESQ    |     |      |      |      |      |      |      |
| Noisy   | 1.44| 1.67 | 1.56 | 59.64| 67.45| 63.55|
| AECNN   | 1.88| 2.20 | 2.04 | 77.37| 85.10| 81.24|
| RHR-Net | 2.06| 2.35 | 2.21 | 78.13| 85.82| 81.98|
| RTNet (Q = 3) | 2.10| 2.37 | 2.23 | 78.59| 85.68| 82.13|
| RTNet (Q = 4) | 2.06| 2.35 | 2.21 | 79.31| 86.20| 82.76|
| RTNet (Q = 5) | 2.09| 2.35 | 2.22 | 79.48| 86.54| 83.01|

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Figure 2: The framework of the proposed network RTNet with recursive learning. (a) The overview of RTNet. \( x, \tilde{s}^{-1}, \tilde{h} \) and \( \tilde{s} \) denote the input feature, the estimation output in stage \( l - 1 \), the state in stage \( l \) and the final estimation output, respectively. (b) The detail of GLU adopted in this study, where PReLU is adopted and the kernel size is set to 11.
to 4 seconds if they exceed 4 seconds and zero-padded on the contrary.

5. Results and analysis

We evaluate the performance of different models in terms of perceptual evaluation of speech quality (PESQ) [33] and short-time objective intelligibility (STOI) [34].

5.1. Objective results comparison

The objective results are presented in Tables 2 and 3. One can observe the following phenomena. Firstly, all the models significantly improve the scores in terms of PESQ and STOI for both seen and unseen cases, whilst the proposed RTNet achieves the best performance among the three models. For example, for seen cases, when \(Q = 3\), RTNet improves PESQ by 0.11 and 0.04, and improves STOI by 0.44% and 0.04% over AECNN and RHR-Net, respectively. This is because the memory mechanism is utilized to refine the network with a stage-wise manner and improve the parameter efficiency. A similar tendency is also observed for unseen cases. Secondly, when comparing between two baselines, RHR-Net obtains consistently better performance than AECNN. This is because BiGRU is adopted as the basic component for both encoding and decoding process, which facilitates better temporal capture capability for long sequences than 1-D Conv, whose performance is limited by kernel size and dilation rate. This can also partly explain the limited advantages of RTNet over RHR-Net.

5.2. The influence of stage number \(Q\)

In this study, we explore the influence of the number of the stages \(Q\), and it takes the values from 1 to 5. The metric improvements are given in Fig. 3. One can observe the following phenomena. Firstly, when \(Q \leq 3\), both PESQ and STOI scores are consistently improved with the increase of \(Q\), indicating that both metrics can be effectively refined with recursive learning. Nonetheless, when \(Q\) takes from 3 to 5, PESQ falls into saturation even slightly attenuation while STOI is further improved. This is because MAE is adopted as the loss criterion, whose optimization target is inconsistent with the objective evaluation criterion and can not further refine both metrics at the same time [35]. This phenomenon reveals that further optimization of MAE can facilitate the STOI but slightly suppress the further optimization of PESQ.

5.3. Insights into recursive learning

To analyze the advantages of recursive learning, we evaluate the metric scores of different intermediate stages when \(Q = 5\) and the results are given in Fig. 4. As the figure shows, when the first recursive stage is finished, the estimation has similar metric scores over the noisy input. However, when the network is recursed for more stages, a notable improvement is observed. This can be explained as the increase of iteration will lead to the accumulation of prior information and it effectively complements the speech details of the current estimation. In addition, as SRNN is formulated with a memory mechanism, it is capable of selectively reserving useful information and dropping irrelevant interference. As a result, the network can better learn how to recover the speech information.

5.4. Trainable parameters and ideal network depth

The number of trainable parameters for the baselines and proposed RTNet is presented in Table 4. One can see that compared with AECNN and RHR-Net, RTNet further decreases the number of trainable parameters, which demonstrates the high parameter efficiency of recursive learning.

To improve network performance, a deeper network is needed, which usually results in more trainable parameters. With recursive learning, the network is reused for multiple stages, and we can explore a deeper network without additional parameters. In this paper, considering the gradient flow, the number of the ideal layers for RTNet is \(28 \times Q\), where 28 represents the number of layers for the feedforward gradient flow. Therefore, a deeper network can be explored by recursing the network for more stages.

6. Conclusions

In this study, we propose a type of recursive network in the time domain named RTNet for monaural speech enhancement. Stage RNN is proposed to effectively aggregate the deep features across different stages. In addition, concatenated GLUs are adopted to increase the receptive field while controlling the information flow. Experimental results demonstrate that RTNet achieves consistently better performance than the other two advanced time-domain baselines and effectively reduces the number of trainable parameters simultaneously.
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