



# Speech Enhancement Using Multi-Stage Self-Attentive Temporal Convolutional Networks

Ju Lin , *Graduate Student Member, IEEE*, Adriaan J. de Lind van Wijngaarden, *Senior Member, IEEE*, Kuang-Ching Wang, *Senior Member, IEEE*, and Melissa C. Smith , *Senior Member, IEEE*

**Abstract**—Multi-stage learning is an effective technique for invoking multiple deep-learning modules sequentially. This paper applies multi-stage learning to speech enhancement by using a multi-stage structure, where each stage comprises a self-attention (SA) block followed by stacks of temporal convolutional network (TCN) blocks with doubling dilation factors. Each stage generates a prediction that is refined in a subsequent stage. A feature fusion block is inserted at the input of later stages to re-inject original information. The resulting multi-stage speech enhancement system, multi-stage SA-TCN, is compared with state-of-the-art deep-learning speech enhancement methods using the LibriSpeech and VCTK datasets. The multi-stage SA-TCN system's hyperparameters are fine-tuned, and the impact of the SA block, the feature fusion block, and the number of stages are determined. The use of a multi-stage SA-TCN system as a front-end for automatic speech recognition systems is also investigated. It is shown that the multi-stage SA-TCN systems perform well relative to other state-of-the-art systems in terms of speech enhancement and speech recognition scores.

**Index Terms**—Speech enhancement, speech recognition, neural networks, self-attention, temporal convolutional networks, multi-stage architectures.

## I. INTRODUCTION

**S**PEECH enhancement is a basic function that is used to improve the quality and intelligibility of a speech signal that is degraded by ambient noise. Speech enhancement algorithms are used extensively in many audio and communication systems, including mobile handsets, speaker verification systems and hearing aids. Popular classic techniques include spectral-subtraction algorithms, statistical model-based methods that use maximum-likelihood (ML) estimators, Bayesian estimators, minimum mean squared error (MMSE) methods, subspace algorithms based on single-value decomposition and noise-estimation algorithms (see [1] and references therein).

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Ju Lin, Kuang-Ching Wang, and Melissa C. Smith are with the Department of Electrical and Computer Engineering, Clemson University, Clemson, SC 29634 USA (e-mail: jul@clemson.edu; kwang@clemson.edu; smithmc@clemson.edu).

Adriaan J. de Lind van Wijngaarden is with the Nokia Bell Labs, Murray Hill, NJ 07974 USA (e-mail: adriaan.de\_lind\_van\_wijngaarden@nokia-bell-labs.com).

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Modern techniques often use deep learning. Early examples include a recurrent neural network (RNN) to model long-term acoustic characteristics [2], and a deep autoencoder that denoises speech signals with greedy layer-oriented pretraining [3]. In [4], a deep neural network (DNN) was used as a nonlinear regression function. In [5], a convolutional recurrent neural network (CRN) was used, consisting of a convolutional encoder-decoder architecture and multiple long short-term memory (LSTM) layers that capture long-context information. Other speech enhancement systems use a generative adversarial network (GAN), which is known for its ability to generate natural-looking signals in the time or frequency domain [6]–[10]. Recent studies consider the use of an attention mechanism [11]–[16]. Self-attention [17] is an efficient context information aggregation mechanism that operates on the input sequence and that can be utilized for any task that has a sequential input and output. In [15], self-attention was combined with a dense convolutional neural network. A time-frequency (T-F) attention method, proposed in [16], combines time-domain and frequency-domain attention to perform denoising and dereverberation simultaneously.

A temporal convolutional network (TCN) consists of dilated 1-D convolutions that create a large temporal receptive field with fewer parameters than other models. Recent research shows that TCN-based models achieve excellent performance for text-to-speech [18], speech enhancement [19]–[23], and speech separation [24]. In [20], a speech enhancement system was proposed that uses a multibranch TCN, MB-TCN, which effectively performs a split-transform-aggregate operation and enables the model to learn and determine an accurate representation by aggregating the information from each branch. In [22], the TCN used in [24] for speech separation was adapted for speech enhancement and integrated into a multilayer encoder-decoder architecture. The use of a complex short-time Fourier transform (STFT) for TCN-based speech enhancement rather than magnitude or time-domain features was investigated in [21].

The above-mentioned methods can generally be classified as feature mapping and mask-learning methods, which are two commonly used deep-learning approaches for single-channel speech enhancement methods for stereo data. Feature mapping approaches enhance the noisy features using a mapping network that minimizes the mean square error between the enhanced and clean features. Mask-learning approaches estimate the ideal ratio mask, the ideal binary mask or the complex ratio mask, and then use this mask to filter noisy speech signals and reconstruct

clean speech signals. Mask-learning methods usually perform better than feature mapping methods in terms of speech quality metrics [25]–[27].

Recently, multi-stage learning has been successfully applied for a wide variety of tasks, including human pose estimation [28], action segmentation [29], speech enhancement [30]–[32] and speech separation [33]. A multi-stage architecture consists of stages that sequentially use the same model or a combination of different models, and each model operates directly on the output of the previous stage. The effect of such an arrangement is that the model used in a given stage takes the predictions from prior stages as input and incrementally refines these predictions.

Multi-stage learning systems that perform the same task in each stage typically use the same supervision principles in each intermediate stage [28], [29], [32]. In [29], multiple stacked TCN networks were proposed for action segmentation. In [32], a multi-stage network with dynamic attention was introduced, where the intermediate output in each stage is corrected with a memory mechanism. To reduce the model parameters, each stage uses a shared network. It was shown that this multi-stage approach typically performs better than systems with a larger and deeper network.

Multi-stage learning systems where each stage performs a different task were considered in [30], [31], [33]. Here, each stage has a different task and a different target. The performance can be improved by aggregating different stages if the nature of each stage is complementary. For instance, a two-stage speech enhancement approach was presented in [30], where the first stage uses a model to predict a binary mask to remove frequency bins that are dominated by severe noise, and where the second stage performs in-painting of the masked spectrogram from the first stage to recover the speech spectrogram that was removed in the first stage. In [31], a two-stage algorithm was proposed to optimize the magnitude and phase separately. The magnitude is optimized in the first stage, and the enhanced magnitude and phase are then further refined jointly.

This paper details a novel multi-stage speech enhancement system, where each stage comprises a self-attention (SA) block [17] followed by stacks of dilated TCN blocks. The system is referred to as a multi-stage SA-TCN speech enhancement system. Each stage generates a prediction in the form of a soft mask that is refined in each subsequent stage. Each self-attention block produces a dynamic representation for different noise environments and their relevance across frequency bins, as such enhancing the features, and the stacks of TCN blocks perform sequential refinement processing. A feature fusion block is inserted at the input of later stages to re-inject original speech information to mitigate possible speech information loss in earlier stages.

This paper is organized as follows. Section II introduces the mathematical notation and details the proposed multi-stage SA-TCN speech enhancement system and the underlying SA, TCN, and feature fusion blocks. The TCN blocks account for the largest contribution to the total number of hyperparameters. Experiments are used later to determine the optimum number of stages and to fine-tune the parameters. Section III details

the comprehensive experiments that were performed using LibriSpeech [34] and VCTK [35] corpus. Section IV first presents the experiments that were performed to fine-tune the multi-stage SA-TCN system's hyperparameters to determine the optimum number of stages, and to quantify the impact of the SA block and the feature fusion block on the performance. It will be shown that the serial multi-stage structure successively refines the predictions. The use of the proposed multi-stage SA-TCN system as a front-end for automatic speech recognition (ASR) systems is also investigated. Extensive experiments with the LibriSpeech [34] and VCTK [35] corpus show that multi-stage SA-TCN systems achieve significantly better speech enhancement and speech recognition scores than other state-of-the-art speech enhancement systems. Section V concludes the paper and discusses further research directions.

## II. MULTI-STAGE SA-TCN SYSTEMS

Speech enhancement systems take a sampled received noisy speech signal as input and reconstructs the speech signal. Let  $\{x(t)|t \in \mathbb{Z}\}$  denote a deterministic discrete-time data sequence that is obtained by sampling a received continuous-time noisy speech signal  $x_c(\cdot)$  at time interval  $T_s$ , i.e.,  $x(t) = x_c(t \cdot T_s) \in \mathbb{R}$ , and let the total number of samples be denoted by  $T_\ell$ . The short-time Fourier transform (STFT) of length  $N$  of  $\{x(t)\}$  with window function  $w(t)$  of length  $N$  and hop-length  $T_h$  is given by

$$X_{\tau,\omega} = \sum_{n=0}^{N-1} w(n)x(\tau T_h + n) \exp\left(-j\frac{2\pi\omega n}{N}\right), \quad (1)$$

where  $\tau$  is the index of the sliding window and  $0 \leq \omega < N$  is the frequency index. In this paper, a Hanning window is used, where

$$w(t) = \sin^2\left(\frac{\pi t}{N-1}\right). \quad (2)$$

Let  $\mathbf{X}$  and  $\mathbf{\Omega}$  denote the STFT magnitude and phase, i.e.,  $\mathbf{X} = \{|X_{\tau,\omega}|\} \in \mathbb{R}^{F \times T}$  and  $\mathbf{\Omega} \in \mathbb{R}^{F \times T}$ , where  $F = N/2 + 1$  denotes the number of frequency bins and  $T = T_\ell/T_h + 1$ .

The proposed multi-stage SA-TCN speech enhancement system consists of  $K$  stages. Fig. 1 illustrates a 4-stage SA-TCN system. Each stage comprises a self-attention (SA) block followed by  $R$  stacks of  $L$  TCN blocks.

Each module has a specific purpose. The  $R$  stacks of  $L$  noncausal TCN blocks, which is particularly suited for temporal sequence modeling, and the skip connection between the input and output of each TCN block reduces the loss of low-level details and provides hooks for optimization. The SA block aggregates context information across frequency bins to obtain a dynamic representation for nonstationary noise conditions.

The multi-stage architecture iteratively refines the initial predictions. It should be noted that the prediction of a previous stage may include some errors. For instance, the frequency bins dominated by speech may be masked and the resulting magnitude spectrogram may lose some of the speech information. A feature fusion block is inserted prior to each stage  $k$ , where  $3 \leq k \leq K$ , which combines the predicted magnitude  $\hat{\mathbf{X}}^{(k-1)}$

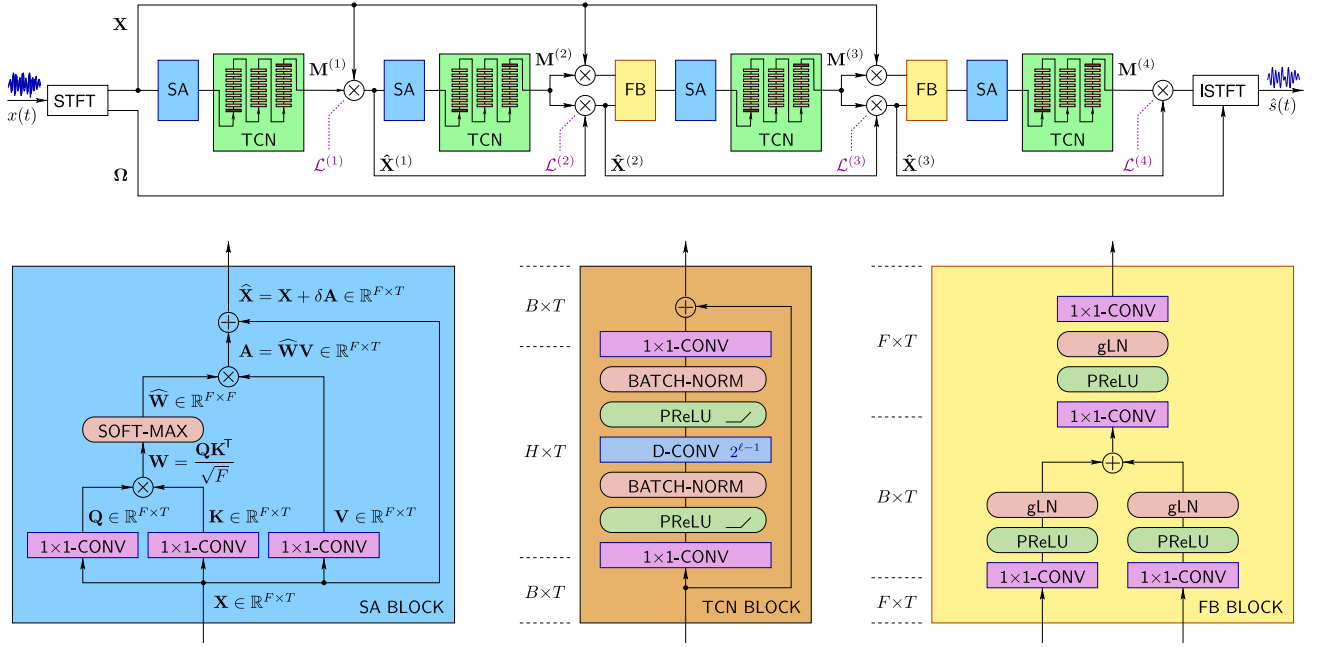


Fig. 1. Block diagram of a multi-stage SA-TCN speech enhancement system with  $K = 4$  stages, where each stage consists of a self-attention (SA) block, followed by  $R = 3$  stacks of  $L = 8$  TCN blocks, where the dilation factor of the  $\ell$ -th TCN block in the stack equals  $\Delta_\ell = 2^{\ell-1}$ , i.e., the dilation doubles for each next TCN block in the stack. A feature fusion block is used as of Stage 3 to re-inject the original masked STFT magnitude. The figure also shows the detailed structure of the self-attention module, with frequency and time dimensions  $F$  and  $T$ , a single TCN block with hyperparameters  $B$ ,  $H$  and  $P$ , and the proposed feature fusion block.

at the output of stage  $k - 1$  and the masked original magnitude  $\mathbf{X}$  as input to re-inject the original speech information.

The first stage consists of a self-attention (SA) block that takes  $\mathbf{X}$  as input and uses three  $1 \times 1$ -convolutions to form the query  $\mathbf{Q}$  and the key-value pair  $(\mathbf{K}, \mathbf{V})$ , where  $\mathbf{Q}, \mathbf{K}, \mathbf{V} \in \mathbb{R}^{F \times T}$ . To compute the attention component  $\mathbf{A}$ , we first compute the weight  $\mathbf{W}$ , given by

$$\mathbf{W} = \frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{F}}, \quad (3)$$

and then use the soft-max function  $\sigma(\cdot)$  to obtain  $\widehat{\mathbf{W}} = \{\widehat{W}_{i,j}\} = \sigma(\mathbf{W})$ , i.e.,

$$\widehat{W}_{i,j} = \frac{\exp(W_{i,j})}{w_j}, \text{ where } w_j = \sum_{i=1}^F \exp(W_{i,j}). \quad (4)$$

The attention component  $\mathbf{A} \in \mathbb{R}^{F \times T}$  is now determined using

$$\mathbf{A} = \widehat{\mathbf{W}}\mathbf{V}, \quad (5)$$

The SA block outputs  $\widehat{\mathbf{X}} = \mathbf{X} + \delta \mathbf{A}$ , where  $\delta$  is a scalar with an initial value of zero that is used to allow the network to first rely on the cues in the local channels  $\mathbf{X}$  and then gradually assign more weight to the nonlocal channels using backpropagation to reach the optimal value.

The output  $\widehat{\mathbf{X}} \in \mathbb{R}^{F \times T}$  is fed into a TCN with input feature dimension  $B$  and network feature map dimension  $H$  by using a bottleneck layer to reduce the number of channels from  $F$  to  $B$ . The TCN consists of  $R$  identical stacks of  $L$  TCN blocks. Each TCN block comprises an  $1 \times 1$  convolution at its input to match the input feature dimension  $B$  to the TCN block's internal feature

map dimension  $H$ , a dilated depthwise convolution (D-conv) layer with kernel size  $P$  and dilation factor  $\Delta_\ell = 2^{\ell-1}$ , where  $\ell$  denotes the order of the TCN block in the stack of  $L$  TCN blocks, and a  $1 \times 1$  convolution layer that reduces the number of channels at the output from  $H$  to  $B$ . This output is then recombined with the input using a skip connection to avoid losing low-level details. A parametric rectified linear unit (PReLU) activation layer [36] and a batch normalization layer [37] are inserted prior to and after the depthwise convolution layer to accelerate training and improve performance. A sigmoid function is applied at the output of the last TCN block of the last stack to obtain a  $[0-1]$  mask  $\mathbf{M}^{(1)}$  that minimizes the mean absolute error loss

$$\mathcal{L}^{(1)} = \|\mathbf{M}^{(1)} \odot \mathbf{X} - \mathbf{S}\|, \quad (6)$$

where the operator  $\odot$  denotes the Hadamard product and  $\mathbf{S}$  denotes the STFT magnitude of the clean speech signal  $s(t)$ .

The stack of  $L$  TCN blocks with kernel  $P$  and dilation factor  $\Delta_\ell = 2^{\ell-1}$  creates a receptive field of size  $R^{(P,L)}$ , given by

$$R^{(P,L)} = 1 + \sum_{\ell=1}^L (P-1) \cdot 2^{\ell-1}. \quad (7)$$

As such, a stack of  $L$  TCN blocks creates a large temporal receptive field with fewer parameters than other models.

This paper considers multi-stage SA-TCN systems with kernel size  $P = 3$ . An illustration of the receptive field for a stack of  $L = 5$  TCN blocks with kernel size  $P = 3$  is shown in Fig. 2. The multi-stage SA-TCN system's hyperparameters  $(B, H, R, L)$  are optimized using experiments.

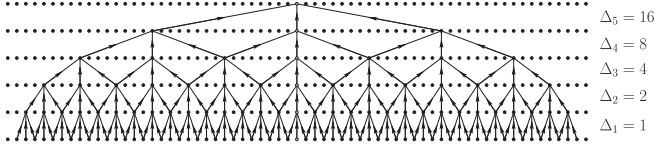


Fig. 2. Example of the connections formed by a noncausal D-convolution for a stack of  $L = 5$  TCN blocks, each with kernel  $P = 3$  and dilation  $\Delta_\ell = 2^{\ell-1}$ , where  $1 \leq \ell \leq L$ .

As indicated, the same SA-TCN structure is used for subsequent stages, and an additional element, a feature fusion block, is inserted prior to each stage if there are three or more stages.

For notational convenience, let  $\Psi_k^{(R,L)}(\cdot)$  denote the mapping performed by the  $R$  stacks of  $L$  TCN blocks in stage  $k$ , and let  $\Upsilon_k(\cdot)$  denote the self-attention operation at stage  $k$ . It follows that  $\mathbf{M}^{(1)}$  can now be expressed as

$$\mathbf{M}^{(1)} = S(\Psi_1^{(R,L)}(\Upsilon_1(\mathbf{X}))), \quad (8)$$

where  $S(\cdot)$  denotes the sigmoid function. As such,  $\mathbf{M}^{(1)}$  is the predicted mask at the output of the first stage. The enhanced speech STFT magnitude  $\hat{\mathbf{X}}^{(1)}$  at the output of stage 1 is given by  $\hat{\mathbf{X}}^{(1)} = \mathbf{M}^{(1)} \odot \mathbf{X}$ .

In a similar fashion, the predicted mask  $\mathbf{M}^{(2)}$  at the output of the second stage can be obtained by evaluating

$$\mathbf{M}^{(2)} = S(\Psi_2^{(R,L)}(\Upsilon_2(\hat{\mathbf{X}}^{(1)}))) \quad (9)$$

and the estimated STFT magnitude  $\hat{\mathbf{X}}^{(2)} = \mathbf{M}^{(2)} \odot \hat{\mathbf{X}}^{(1)}$ .

A multi-stage SA-TCN speech enhancement system with three or more stages ( $K \geq 3$ ) is constructed by inserting a feature fusion block that performs operation  $\Phi(\cdot)$  prior to each stage  $k$ , taking the masked STFT magnitude  $\hat{\mathbf{X}}^{(k-1)}$  and STFT magnitude  $\mathbf{X}$  as inputs. Each input is passed through a  $1 \times 1$ -convolution and a PReLU operation, after which global layer normalization (gLN) is performed [24]. The operation  $gLN(\mathbf{Y})$  is given by

$$gLN(\mathbf{Y}) = \frac{\mathbf{Y} - E[\mathbf{Y}]}{\sqrt{\text{var}(\mathbf{Y}) + \epsilon}} \odot \gamma + \beta, \quad (10)$$

where  $\mathbf{Y} \in \mathbb{R}^{F \times T}$  is the input feature with mean  $E[\mathbf{Y}]$  and variance  $\text{var}(\mathbf{Y})$ ,  $\gamma, \beta \in \mathbb{R}^{F \times 1}$  are trainable parameters, and  $\epsilon$  is a small constant for numerical stability.

The outputs of the two gLN are added, and the result is again sent through a  $1 \times 1$ -convolution, a PReLU, another gLN, another  $1 \times 1$ -convolution and another PReLU. The output, denoted as  $\check{\mathbf{X}}^{(k-1)}$ , is given by

$$\check{\mathbf{X}}_{k-1} = \Phi_k(\mathbf{M}^{(k-1)} \odot \mathbf{X}, \hat{\mathbf{X}}^{(k-1)}). \quad (11)$$

The output  $\check{\mathbf{X}}_{k-1}$  is then used as an input to the next stage, and the expression for the mask  $\mathbf{M}^{(k)}$  at the output of the  $k$ -th stage is now given by

$$\mathbf{M}^{(k)} = S(\Psi_k^{(R,L)}(\Upsilon_k(\check{\mathbf{X}}_k))). \quad (12)$$

The enhanced magnitude  $\hat{\mathbf{X}}^{(k)}$  at stage  $k$  is given by

$$\hat{\mathbf{X}}^{(k)} = \mathbf{M}^{(k)} \odot \hat{\mathbf{X}}^{(k-1)}. \quad (13)$$

Each next stage  $k$ , where  $k > 1$ , computes mask  $\mathbf{M}^{(k)}$  that minimizes the mask-based signal approximation mean absolute error loss  $\mathcal{L}^{(k)}$  using

$$\mathcal{L}^{(k)} = \|\mathbf{M}^{(k)} \odot \hat{\mathbf{X}}^{(k-1)} - \mathbf{S}\|, \quad (14)$$

where  $\hat{\mathbf{X}}^{(k-1)}$  denotes the estimated STFT magnitude at stage  $k-1$ .

At the output of the last stage of the multi-stage SA-TCN system, the time-domain waveform  $\hat{s}$  is computed using the processed STFT magnitude  $\hat{\mathbf{X}}^{(K)}$  and the original STFT phase  $\Omega$  by applying the inverse STFT, in short ISTFT, denoted as

$$\hat{s} = \text{ISTFT}(\hat{\mathbf{X}}^{(K)}, \Omega). \quad (15)$$

The proposed multi-stage SA-TCN system provides a mean absolute error loss  $\mathcal{L}^{(k)}$  at the output of each stage. Since each stage provides an equal contribution during the training process, we use the accumulated mask-based signal approximation training objective function

$$\mathcal{L} = \sum_{k=1}^K \mathcal{L}^{(k)}. \quad (16)$$

The use of the mean absolute error loss is motivated by recent observations that it achieves better objective quality scores when using spectral mapping techniques [38], [39].

### III. EXPERIMENTAL SETUP

In the following, the dataset, model setup and evaluation metrics are detailed.

#### A. Dataset

To verify the effectiveness of the proposed multi-stage SA-TCN system, we conduct experiments using the LibriSpeech and VCTK datasets. The detailed setup for each dataset is detailed below.

**LibriSpeech** is an open-source corpus that contains 960 hours of speech derived from audiobooks in the LibriVox project. The sampling frequency is 16 kHz. The clean source is trained using 100 hours of speech data from the “train-clean” dataset. The validation set uses 800 sentences from the “dev-clean” dataset, and the test set uses 500 sentences from the “test-clean” dataset. The training set uses 10,000 randomly selected noise sample sequences from the DNS Challenge [40]. The training clean speech was cut to 75,206 4-second segments. The training and validation sets distort the clean segments with a randomly selected noise sound from the DNS Challenge noise set with an SNR in the set  $\{-5, -4, \dots, 9, 10\}$  (in dB). The test set uses three distinct noise types: “babble noise” from the NOISEX-92 corpus [41], and “office noise” and “kitchen noise” from the DE-MAND noise corpus [42]. The first channel signal of the corpus is used for data generation. Each clean utterance is distorted by a randomly selected noise type at a randomly selected SNR from the set  $\{-5, 0, 5, 10, 15\}$  (in dB).

The **VCTK** database used here is derived from the Valentini-Botinhao corpus [35]. Each speaker fragment contains approximately 10 different sentences. The training set uses 28 speakers,



and the test set uses two speakers. The training set used here uses 40 noise conditions: eight noise types and two artificial noise types from the Demand database [42]) are used at a randomly selected SNR from the set  $\{0, 5, 10, 5\}$  (in dB). The test set uses 20 noise conditions: five noise types from the Demand database at a randomly selected SNR from the set  $\{2.5, 7.5, 12.5, 17.5\}$  (in dB). There are approximately 20 different sentences in each condition for each test speaker. The test set conditions are different from the training set, as the test set uses different speakers and noise conditions.

### B. Model Setup

The baseline systems used for performance comparison are a CRN system [5], a complex-CNN system that is based on concepts proposed in [43] and that was adapted for speech enhancement, and a multi-stage system DARN [32]. The setup of the baseline systems and the proposed multi-stage SA-TCN systems are detailed below.

**CRN:** The CRN-based approach takes the magnitude as input. Instead of directly mapping the noisy magnitude to the clean magnitude, we adapted the CRN to predict the ratio mask and as such improved its performance. The CRN-based method consists of five 2D convolution layers with filters of size  $3 \times 2$  each and [16, 32, 64, 128, 256] output channels, respectively. This output is postprocessed by two LSTM layers with 1024 nodes each, and five 2D deconvolution layers with filter size  $3 \times 2$  each and output channels [128, 64, 32, 16, 1], respectively.

**Complex-CNN:** The complex-CNN performs a complex spectral mapping [44], [45], where the real and imaginary spectrograms of the noisy speech signal are treated as two different input channels. An STFT is used with a 20 ms Hanning window, a 20 ms filter length and a 10 ms hop size. The architecture uses eight convolutional layers, one LSTM layer and two fully connected layers, each with ReLU activations except for the last layer, which has a sigmoid activation. The parameters used here are similar to those used in [43], but now both the input and the output have two channels with real and imaginary components, respectively. The prediction serves as a complex mask, consisting of a real and imaginary mask. The training stage uses a multiresolution STFT loss function [46], which is the sum of all STFT loss functions using different STFT parameters.

**DARN:** DARN [32] is a recently proposed monaural speech enhancement technique that uses multiple stages and combines dynamic attention and recursive learning. Experiments are conducted with open-source code<sup>1</sup> using a noncausal, 3-stage configuration.

**Proposed multi-stage SA-TCN Systems:** The proposed multi-stage SA-TCN systems are characterized by the number of stages  $K$  and the hyperparameters  $(H, B, R, L)$ . Each  $K$ -stage SA-TCN system uses an STFT with a 32 ms Hanning window, a 32 ms filter length and a 16 ms hop size. As such,  $F = 257$ . The multi-stage SA-TCN systems are trained using 80 epochs of 4-second utterances from the LibriSpeech corpus and using 100 epochs of variable-length utterances from the VCTK corpus.

The proposed multi-stage SA-TCN systems are trained using the Adam optimizer [47] with an initial learning rate of 0.0002. All models use a minibatch of 16 utterances. For each minibatch of 16 utterances from the VCTK corpus, the longest utterance is determined, and the other utterances are zero-padded to obtain equal-length utterances.

### C. ASR Setup

Automatic speech recognition (ASR) experiments use a time-delay neural network-hidden Markov model (TDNN-HMM) hybrid chain model [48]. The TDNN models long-term temporal dependencies with training times that are comparable to standard feed-forward DNNs. The data are represented at different time points by adding a set of delays to the input, which allows the TDNN to have a finite dynamic response to the time-series input data. This acoustic model is trained using the Kaldi toolkit [49] with the standard recipe.<sup>2</sup> The ASR acoustic models were trained using 960 hours from the LibriSpeech training set. The word error rate (WER) was measured using LibriSpeech's "test-clean" set.

### D. Evaluation Metrics

Speech enhancement systems are evaluated using the commonly used wide-band *perceptual evaluation of speech quality* (PESQ) score [50]–[52], the *short-time objective intelligibility* (STOI) score [53], the scale-invariant signal-to-distortion ratio (SI-SDR) [54], and the CSIG, CBAK and COVL scores. The CSIG score is a signal distortion mean opinion score, the CBAK score measures background intrusiveness, and the COVL score measures the speech quality. The automatic speech recognition performance is measured by determining the word error rate (WER).

## IV. EXPERIMENTAL PERFORMANCE RESULTS

Extensive experiments have been performed to determine the performance of the proposed multi-stage SA-TCN speech enhancement systems. This section first details the findings of the ablation studies and then presents the performance results for the multi-stage SA-TCN systems.

### A. Ablation Studies

Ablation studies were performed to fine-tune the multi-stage SA-TCN system's hyperparameters  $(H, B, R, L)$  and to analyze the effectiveness of the self-attention and feature fusion blocks.

The performance of 5-stage SA-TCN systems is measured in terms of PESQ and STOI scores for several hyperparameter configurations. The results are listed in Table I. We observe that it is more effective to increase the number of channels (hyperparameters  $B$  and  $H$ ) in each TCN block than to increase the number of TCN blocks per stack ( $L$ ). For instance, when  $R = 2$  and  $H$  and  $B$  are doubled, the PESQ score improves from 2.59 to 2.65, and the STOI score improves from 92.36

<sup>1</sup>[Online]. Available: <https://github.com/Andong-Li-speech/DARN>

<sup>2</sup>[Online]. Available: <https://github.com/kaldi-asr/kaldi/tree/master/egs/librispeech/s5>

TABLE I  
PERFORMANCE FOR SEVERAL 5-STAGE SA-TCN CONFIGURATIONS

$R$	$L$	$H$	$B$	$P$	model size	PESQ	STOI
2	5	128	64	3	2.38 M	2.59	92.36
2	5	256	128	3	5.19 M	2.65	93.02
2	8	128	64	3	2.90 M	2.53	92.32
2	8	256	128	3	7.21 M	2.64	93.05
3	5	128	64	3	2.81 M	2.61	92.67
3	5	256	128	3	6.88 M	2.71	<b>93.40</b>
3	8	128	64	3	3.59 M	2.60	92.20
3	8	256	128	3	9.91 M	<b>2.73</b>	93.37

The best score in a column is bold-faced.

TABLE II  
PER-STAGE PESQ AND STOI SCORES FOR A 5-STAGE SA-TCN SYSTEM

Stage	PESQ	STOI
stage 1	2.60	93.08
stage 2	2.65	93.10
stage 3	2.70	93.22
stage 4	2.72	93.33
stage 5	2.73	93.37

to 93.02. Additionally, using  $L = 8$  instead of  $L = 5$  causes a slight degradation of the PESQ score. The performance can also be improved significantly by increasing the number of stacks  $R$ . We determined the model size for the larger TCN with  $R = 3$  stacks and  $L = 8$  TCN blocks per stack, which accounts for approximately 1.68 M parameters. Each SA block has approximately 0.2 M parameters, and each feature fusion block has approximately 0.17 M parameters. If we only consider models with fewer than 10 million parameters, the model where  $(H, B, R, L) = (256, 128, 3, 8)$  performs best. We should also note that there is a trade-off between the performance and the model size.

Next, we investigate the contribution of each stage to the performance of a 5-stage SA-TCN speech enhancement system. The motivation for employing multi-stage learning is that the initial prediction is refined by the next stage. The results in Table II show that the performance improves stepwise after each stage. For instance, when comparing the first and fifth stages shows that the PESQ score improves from 2.60 to 2.73, and the STOI score improves from 93.08% to 93.37%. We also observe that the PESQ score's rate of improvement gradually decreases from 0.5 to 0.1, which suggests that adding further stages has diminishing returns in terms of performance and that a 5-stage SA-TCN system is likely close to the upper bound on performance for this multi-stage TCN-based approach.

The performance impact of using self-attention was determined using PESQ and STOI scores. The results are shown in Fig. 3. On average, a 5-stage SA-TCN system provides an STOI score improvement of 3.5% and a PESQ score improvement of 1.05 relative to unprocessed noisy speech. The insertion of the SA block prior to the stacked layers of TCN blocks consistently improves PESQ and STOI scores for all SNR conditions: the average PESQ score improves from 2.68 to 2.73, and the average STOI score improves from 93.16% to 93.37%. This indicates

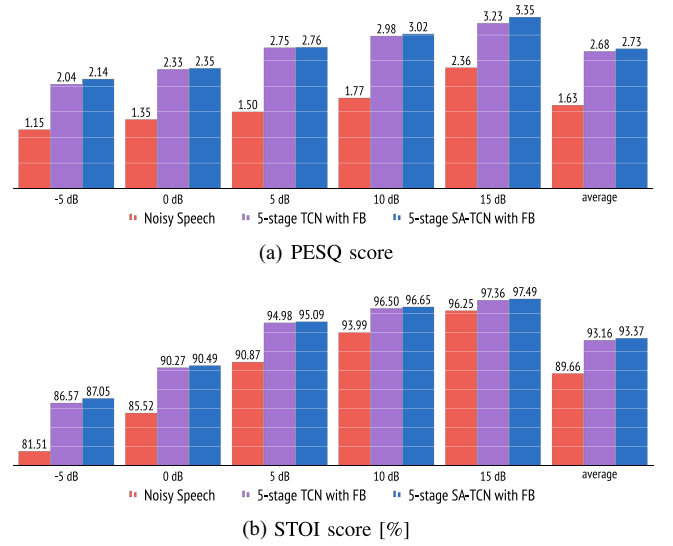


Fig. 3. Impact of using a self-attention module in a 5-stage SA-TCN system, where  $(H, B, R, L) = (256, 128, 3, 8)$ .

that the SA block can aggregate the frequency context, which is helpful for TCN-based speech enhancement. We observe that the attention is activated in different frequency bins, e.g., for babble noise, low-frequency bins are activated. We also observe that the use of SA blocks show more significant performance gains at low SNR, e.g., at  $-5$  dB, the PESQ score improves from 2.04 to 2.14 and the STOI score improves from 86.57% to 87.05%. This also indicates that multi-stage SA-TCN systems are more robust for lower SNR.

The effectiveness of the proposed feature fusion block, which re-injects original information in stages 3–5 in a 5-stage SA-TCN system to alleviate any speech signal loss, is considered next. The PESQ and STOI scores are shown in Fig. 4, which shows that both scores improve for all SNR scenarios. The average PESQ score improves from 2.65 to 2.73, and the average STOI score improves from 93.08% to 93.37%. The impact of the feature fusion block is, as expected, more prominent at lower SNR, when the model not only removes the noise but can also easily partly remove the speech signal.

### B. Baseline System Comparison

Extensive experiments with the proposed multi-stage SA-TCN system and the CRN-based, complex-CNN and DARN systems were conducted using the LibriSpeech dataset. All multi-stage SA-TCN systems use hyperparameters  $(H, B, R, L) = (256, 128, 3, 8)$ . Table III shows that all multi-stage SA-TCN systems outperform the baseline systems in terms of the PESQ score for the different noise types and SNR conditions. The results also show that multi-stage SA-TCN systems with more stages have a better PESQ score. Similarly, Table IV shows that the STOI scores of the multi-stage SA-TCN systems are generally better than the baseline systems and that the best STOI scores are generally obtained for 4-stage and 5-stage SA-TCN systems. Interestingly, even the single-stage

TABLE III  
PESQ SCORES FOR MULTI-STAGE SA-TCN AND BASELINE SYSTEMS USING SAMPLES FROM THE LIBRISPEECH CORPUS

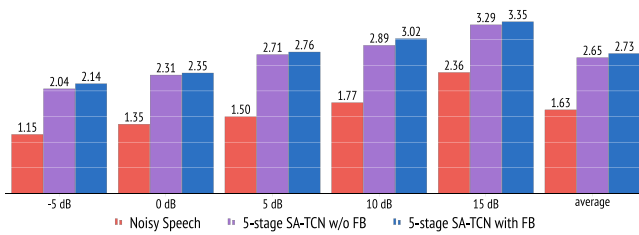
Noise type	Office Noise					Babble Noise					Kitchen Noise					Average
SNR	-5	0	5	10	15	-5	0	5	10	15	-5	0	5	10	15	
Noisy speech	1.30	1.68	2.01	2.60	3.39	1.06	1.09	1.22	1.37	1.80	1.07	1.18	1.30	1.62	2.10	1.63
CRN	1.90	2.16	2.58	3.07	3.45	1.08	1.20	1.46	1.75	2.24	1.43	1.81	2.19	2.44	2.78	2.09
Complex-CNN	2.14	2.40	2.84	3.01	3.24	1.13	1.30	1.70	2.06	2.54	1.77	2.20	2.46	2.67	2.95	2.30
DARCN	2.23	2.48	3.02	3.35	3.62	1.14	1.33	1.72	1.97	2.52	1.80	2.16	2.45	2.64	2.82	2.35
1-stage SA-TCN	2.29	2.60	3.11	3.38	3.64	1.15	1.38	1.85	2.28	2.81	1.83	2.27	2.69	2.84	2.87	2.47
2-stage SA-TCN	2.55	2.85	<b>3.46</b>	<b>3.65</b>	<b>3.84</b>	1.17	1.44	1.94	2.37	2.89	1.93	2.47	2.94	3.09	<b>3.39</b>	2.67
3-stage SA-TCN	2.67	<b>2.93</b>	3.43	3.58	3.83	1.17	1.42	1.97	2.39	2.92	1.95	2.47	2.94	3.18	3.30	2.69
4-stage SA-TCN	2.61	2.90	3.42	3.56	3.81	<b>1.19</b>	1.46	2.03	2.48	2.95	1.97	2.49	<b>2.98</b>	3.11	3.35	2.70
5-stage SA-TCN	<b>2.74</b>	2.90	3.38	3.57	3.82	1.18	<b>1.47</b>	<b>2.05</b>	<b>2.51</b>	<b>3.02</b>	<b>2.10</b>	<b>2.53</b>	2.94	<b>3.19</b>	3.30	<b>2.73</b>

All multi-stage SA-TCN models use hyperparameters  $(H, B, R, L) = (256, 128, 3, 8)$ . The best score in a column is bold-faced.

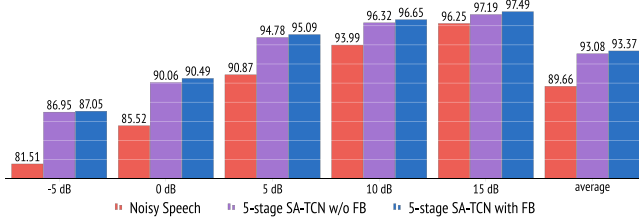
TABLE IV  
STOI SCORES FOR MULTI-STAGE SA-TCN AND BASELINE SYSTEMS USING SAMPLES FROM THE LIBRISPEECH CORPUS

Noise type	Office Noise					Babble Noise					Kitchen Noise					Average
SNR [dB]	-5	0	5	10	15	-5	0	5	10	15	-5	0	5	10	15	
Noisy speech	92.91	96.81	98.50	98.62	99.25	54.94	64.93	80.04	87.10	91.08	84.59	91.75	95.40	98.21	98.86	89.66
CRN	93.02	96.15	97.29	97.55	98.07	54.44	68.15	83.75	90.04	91.98	87.14	92.60	95.57	97.15	97.23	90.23
Complex-CNN	93.23	95.78	97.25	96.91	97.01	60.70	72.92	87.01	91.85	93.26	87.38	92.63	95.11	96.83	96.83	91.09
DARCN	95.08	97.04	98.46	98.44	98.82	62.60	75.20	88.90	91.72	94.41	90.31	93.71	96.60	<b>98.31</b>	98.31	92.64
1-stage SA-TCN	94.81	97.09	98.55	98.52	98.76	61.51	74.96	88.62	92.89	94.26	89.37	94.11	96.37	98.08	98.27	92.52
2-stage SA-TCN	94.85	96.98	98.35	98.24	98.89	64.91	76.59	89.89	93.29	94.47	89.45	93.72	96.76	97.67	98.65	92.88
3-stage SA-TCN	95.02	97.23	98.48	98.32	98.92	63.30	75.75	89.92	93.63	94.64	88.71	93.68	96.79	98.12	98.60	92.82
4-stage SA-TCN	94.93	97.14	98.52	98.22	98.75	<b>65.47</b>	76.94	<b>90.33</b>	93.70	94.73	89.41	94.47	96.74	98.10	98.62	93.10
5-stage SA-TCN	<b>95.43</b>	<b>97.24</b>	<b>98.62</b>	<b>98.60</b>	<b>98.96</b>	64.26	<b>77.57</b>	<b>90.33</b>	<b>93.94</b>	<b>94.94</b>	<b>90.82</b>	<b>94.84</b>	<b>96.88</b>	98.22	<b>98.78</b>	<b>93.37</b>

All multi-stage SA-TCN models use hyperparameters  $(H, B, R, L) = (256, 128, 3, 8)$ . The best score in a column is bold-faced.



(a) PESQ score



(b) STOI score [%]

Fig. 4. Impact of using a feature fusion block in a 5-stage SA-TCN system, where  $(H, B, R, L) = (256, 128, 3, 8)$ .

SA-TCN system outperforms all baseline systems in terms of the PESQ score. Adding more stages significantly improves the overall performance. For instance, the single-stage SA-TCN and the 2-stage SA-TCN have average PESQ scores of 2.47 and 2.67, respectively, and average STOI scores of 92.52% and

TABLE V  
SI-SDR SCORES FOR MULTI-STAGE SA-TCN AND BASELINE SYSTEMS USING SAMPLES FROM THE LIBRISPEECH CORPUS

SNR [dB]	-5	0	5	10	15	Average
CRN	1.43	5.72	9.63	13.07	16.39	9.28
Complex-CNN	9.66	11.32	13.35	14.49	16.86	13.15
DARCN	11.00	12.65	15.84	17.60	19.87	15.41
1-stage SA-TCN	11.13	<b>13.40</b>	16.77	18.05	19.77	15.84
2-stage SA-TCN	10.80	12.71	16.60	17.42	19.44	15.42
3-stage SA-TCN	11.41	13.03	<b>17.01</b>	<b>18.34</b>	<b>20.33</b>	<b>16.04</b>
4-stage SA-TCN	10.48	12.69	16.25	17.10	19.51	15.23
5-stage SA-TCN	<b>11.43</b>	12.82	16.29	17.41	19.67	15.55

The best score in a column is bold-faced.

92.88%. The best performance is achieved with  $K = 5$  stages, with an average PESQ score of 2.73 and an average STOI score of 93.37%. The proposed 5-stage SA-TCN system has much better PESQ and STOI scores than the baseline systems, which demonstrates the effectiveness of the proposed approach. We also observe that multi-stage learning is more effective at a low SNR. For example, the 5-stage SA-TCN system achieves much better performance for Office and Kitchen Noise at  $-5$  dB, and it also performs well for Babble Noise at low SNR.

Finally, we determined the SI-SDR metrics that quantify speech distortion. Table V shows that the proposed multi-stage SA-TCN systems generally outperform the baseline systems. We also observe that the SI-SDR performance for multi-stage

TABLE VI  
SPEECH RECOGNITION PERFORMANCE OF MULTI-STAGE SA-TCN AND  
BASELINE SYSTEMS

Method	WER [%]	WER reduction [%]
Noisy Speech	32.94	—
CRN	30.86	6.3
Complex-CNN	27.44	16.7
DARCN	26.18	20.5
1-stage SA-TCN	27.86	15.4
2-stage SA-TCN	25.32	23.1
3-stage SA-TCN	26.11	20.7
4-stage SA-TCN	25.27	23.3
5-stage SA-TCN	<b>24.67</b>	<b>25.1</b>

The best score in a column is bold-faced.

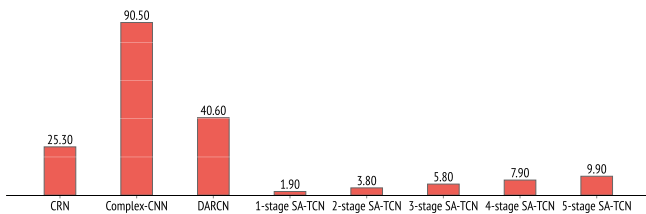


Fig. 5. The number of MAC operations for the proposed and baseline systems.

SA-TCN systems with  $K > 3$  stages decreases slightly, which indicates that the additional stages not only mask the noise but also distort the speech signal. However, it is shown next that these speech distortions do not impact the ASR performance.

### C. Automatic Speech Recognition

We conducted automatic speech recognition (ASR) experiments using LibriSpeech to assess the performance of multi-stage SA-TCN systems with up to five stages and determined the word error rate (WER) as well as the WER reduction. The baseline systems are the CRN-based method, and the complex-CNN and DARCN methods. The results are shown in Table VI. Our 1-stage SA-TCN system performs slightly worse than the best baseline systems, but the multi-stage SA-TCN methods perform better, and the proposed 5-stage SA-TCN achieves an absolute improvement of 18.8%, 8.4% and 4.6% relative to the CRN, complex-CNN and DARCN methods, respectively. The ASR results are similar to the STOI performance.

### D. Model Complexity

The model complexity is determined for all models using an open-source toolbox that counts the number of multiply-accumulate (MAC) operations.<sup>3</sup> Fig. 5 shows the number of MAC operations that are performed to process one time frame. The proposed models clearly have a significantly lower computational complexity than the baseline systems.

<sup>3</sup>[Online]. Available: <https://github.com/Lyken17/pytorch-OpCounter>

### E. Spectrogram-Based Visualization

Speech enhancement performance can be assessed using spectrograms. Consider the situation where clean speech is perturbed by Babble Noise at an SNR of 5 dB. Fig. 6 shows spectrograms of the noisy speech signal, clean speech target, as well as CRN-based and complex-CNN-based systems, the DARCN system, and the proposed 5-stage SA-TCN enhanced speech system. The spectrograms clearly show that the proposed system is best at suppressing residual noise while preserving the speech patterns.

### F. Estimated Mask Visualization

The estimated masks of each stage of a 5-stage SA-TCN system are shown in Fig. 7. We observe that the first stage masks most of the noise and that the later stages successively refine prior predictions in different frequency regions.

### G. Speech-Enhancement Benchmark Results

The proposed multi-stage SA-TCN speech enhancement systems are compared with state-of-the-art methods using the publicly available benchmark dataset VCTK. As shown in Table VII, the proposed multi-stage SA-TCN systems outperform methods that use T-F frequency features, including magnitude, gamma-tone spectral and complex STFT in terms of all speech enhancement metrics used in this paper. Compared with the recently proposed time-domain method DEMUCS, our proposed method uses fewer parameters and achieves better performance in terms of CBAK and COVL metrics, while the PESQ, STOI and CSIG are slightly worse. The experiments with the VCTK corpus show that adding more stages still provides some incremental performance improvements.

## V. DISCUSSION AND CONCLUSION

In this paper, we presented novel multi-stage SA-TCN speech enhancement systems, where each stage consists of a self-attention block followed by  $R$  stacks of  $L$  temporal convolutional network blocks with doubling dilation factors. The stacks of  $L$  TCN blocks effectively perform sequential refinement processing. Multi-stage SA-TCN systems with three or more stages use a feature fusion block as of the third stage to mitigate any possible loss of the original speech information loss in later stages. The proposed self-attention module is used to provide a dynamic representation by aggregating the frequency context. Extensive experiments were used to fine-tune the hyperparameters. It was shown that both the addition of the self-attention modules and the feature fusion blocks resulted in better performance. We noted that even the basic 1-stage SA-TCN system performs well and that adding stages improves speech enhancement scores. The model size increases almost linearly with the number of stages. The relative improvement when adding an additional stage reduces when more stages are added and as such, one approaches an implicit upper bound for this approach. The best overall performance with a reasonable model size was obtained with a 5-stage SA-TCN system.



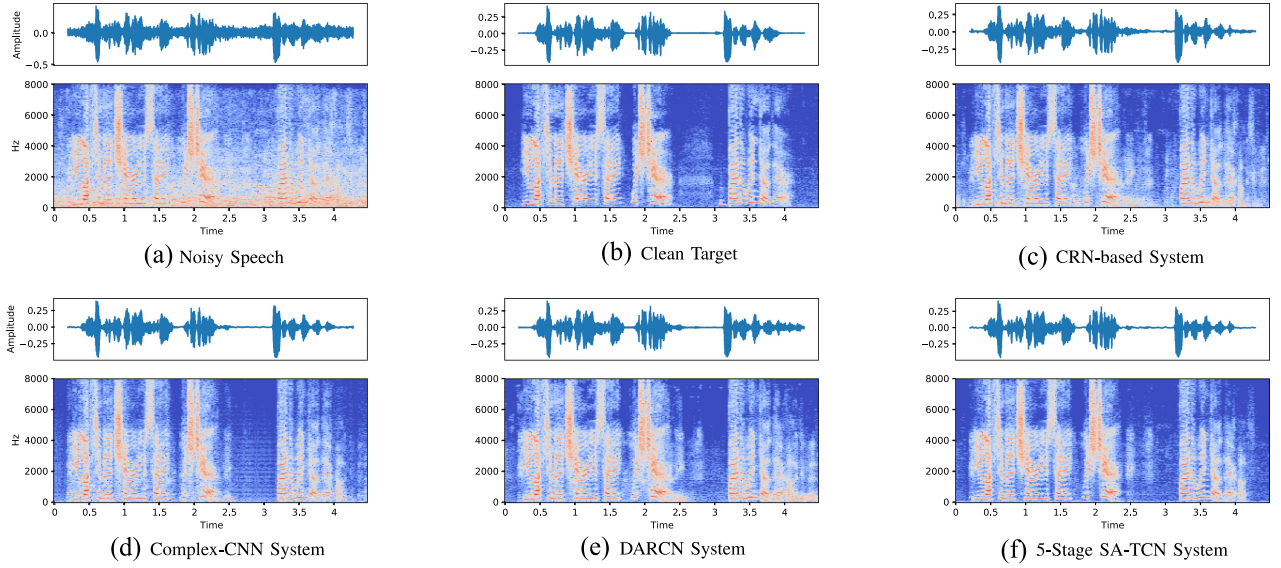


Fig. 6. Spectrograms of a sample input mixed with babble noise at an SNR of 5 dB and the speech-enhanced signals at the output of SA-TCN and baseline systems.

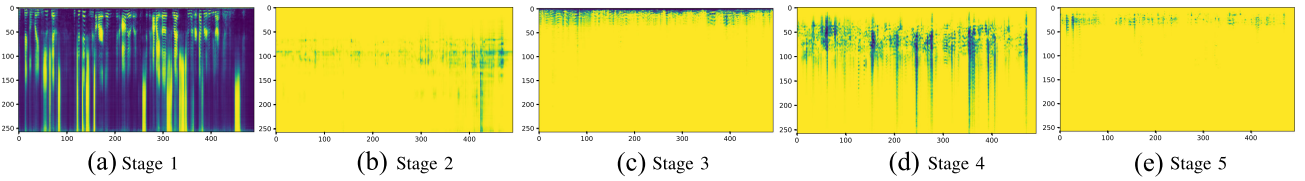


Fig. 7. Estimated masks of each stage for a 5-stage SA-TCN system.

TABLE VII  
PERFORMANCE EVALUATION SCORES OF MULTI-STAGE SA-TCN AND BASELINE SYSTEMS USING SAMPLES FROM THE VCTK CORPUS

	model size	feature type	PESQ	STOI	CSIG	CBAK	COVL	SI-SDR
noisy speech	—	—	1.97	0.921	3.35	2.44	2.63	8.45
SEGAN [6] (2017)	43.2 M	Waveform	2.16	0.93	3.48	2.94	2.80	—
Wave-U-Net [55] (2018)	10.2 M	Waveform	2.40	—	3.52	3.24	2.96	—
DFL [56] (2018)	0.64 M	Waveform	—	—	3.86	3.33	3.22	—
MMSE-GAN [57] (2018)	0.79 M	Gamma-tone spectral	2.53	0.93	3.80	3.12	3.14	—
MetricGAN [7] (2019)	1.89 M	Magnitude	2.86	—	3.99	3.18	3.42	—
MB-TCN [20] (2019)	1.66 M	Magnitude	2.94	0.9364	4.21	3.41	3.59	—
DeepMMSE [58] (2020)	—	Magnitude	2.95	0.94	4.28	3.46	3.64	—
MHSA-SPK [14] (2020)	—	STFT	2.99	—	4.15	3.42	3.57	—
STFT-TCN [21] (2020)	—	STFT	2.89	—	4.24	3.40	3.56	—
DEMUCS [46] (2020)	127.9 M	Waveform	<b>3.07</b>	<b>0.95</b>	<b>4.31</b>	3.40	3.63	—
1-stage SA-TCN	1.88 M	Magnitude	2.84	0.9402	4.16	3.37	3.50	17.98
2-stage SA-TCN	3.76 M	Magnitude	2.96	0.9422	4.25	3.45	3.62	18.19
3-stage SA-TCN	5.81 M	Magnitude	2.99	0.9423	4.27	3.48	3.64	18.38
4-stage SA-TCN	7.86 M	Magnitude	3.01	0.9428	4.27	3.49	3.66	18.40
5-stage SA-TCN	9.91 M	Magnitude	3.02	0.9439	4.29	<b>3.50</b>	<b>3.67</b>	<b>18.48</b>

The best score in a column is bold-faced.

Extensive experiments were conducted using the LibriSpeech and VCTK data sets to determine the performance of the multi-stage SA-TCN speech enhancement systems and to compare the proposed system with other state-of-the-art deep-learning speech enhancement systems. It was shown that the proposed

multi-stage SA-TCN methods achieve better performance in terms of widely used objective metrics while having fewer parameters. Speech enhancement, especially in mobile applications, requires computational- and parameter-efficient models. As shown in Fig. 5, the proposed methods have less

computational cost and simultaneously provide excellent performance. Spectrograms were used to visualize that the proposed 5-stage SA-TCN systems can remove noise effectively while preserving the speech patterns. The proposed multi-stage SA-TCN systems predict a soft mask at each stage, which can be viewed as an implicit ideal ratio mask (IRM). For speech signals that are dominated by noise, the noise is suppressed gradually in each stage, which is the main reason for the excellent performance. The proposed multi-stage SA-TCN systems were also shown to have excellent ASR performance.

The focus of this paper was to process and enhance the spectrum magnitude, and the unaltered noisy phase was used when reconstructing the waveforms in the time domain. Recently, several studies have shown that phase information is also important for improving the perceptual quality [31], [59]. Thus, incorporating phase information into the proposed approach may lead to further improvements. This is currently being investigated.

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**Ju Lin** (Graduate Student Member, IEEE) received the M.S. degree in computer science from Beijing Language and Culture University (BLCU), China, in 2017. He is a Ph.D. Candidate with Clemson University, Clemson, SC, USA. During his studies, he was a member of BLCU's Speech Acquisition and Intelligent Technology (SAIT) Laboratory. His research interests include speech recognition, prosody modeling, speech enhancement and computer-assisted language learning.



**Adriaan J. de Lind van Wijngaarden** (Senior Member, IEEE) received the Engineering degree in electrical engineering from the Eindhoven University of Technology, The Netherlands, in 1992, and the Doctorate degree in engineering from the University of Essen, Germany, in 1998. He is a Technical Staff Member with Bell Labs, Nokia, in Murray Hill, NJ, USA. He joined the Mathematics of Communications Research Department, Bell Labs, Murray Hill (1998–2014), and is currently with Bell Labs Access Research, where he is deeply engaged in theoretical

and application-driven research in communications, information theory and coding. He has provided key contributions to high-speed optical and broadband copper, optical, and wireless access systems. He has authored more than 78 technical papers and holds more than 64 patents.

Dr. De Lind van Wijngaarden was a Publication Editor (2005–2008) and an Associate Editor (2008–2011) for the IEEE TRANSACTIONS INFORMATION THEORY. He has held IEEE leadership positions with the region, council, section and chapter levels, and in IEEE MGA/USA committees. He was the co-recipient of the 2010 Broadband Infovision Award, 2011 Bell Labs President Award, 2014 IEEE COMSOC Globecom Best Industry Paper Award, 2014 GreenTouch 1000X Award and several IEEE Service Awards.



**Kuang-Ching Wang** (Senior Member, IEEE) received the B.S. and M.S. degrees in electrical engineering from National Taiwan University, Taiwan, in 1997 and 1999, respectively, and the M.S. and Ph.D. degrees in electrical and computer engineering from the University of Wisconsin, Madison, WI, in 2001 and 2003, respectively. He is a Professor of Electrical and Computer Engineering and the Associate Director of Research for the Watt Family Innovation Center with Clemson University. His current research interests include wireless networks and mobile computing, ad hoc and sensor networks, distributed protocols, pervasive applications, embedded systems, and artificial intelligence.



**Melissa C. Smith** (Senior Member, IEEE) received the B.S. and M.S. degrees in electrical engineering from Florida State University, Tallahassee, FL, USA, in 1993 and 1994, respectively, and the Ph.D. degree in electrical engineering from the University of Tennessee, Knoxville, TN, USA, in 2003. She is currently a Professor of Electrical and Computer Engineering with Clemson University, Clemson, SC, USA. She has more than 25 years of experience developing and implementing scientific workloads and machine learning applications across multiple domains, including 12 years as a Research Associate with Oak Ridge National Laboratory. Her current research focuses on the performance analysis and optimization of emerging heterogeneous computing architectures (GPGPU- and FPGA-based systems) for various application domains, including machine learning, high-performance or real-time embedded applications, and image processing. Her group collaborates with researchers in other fields to develop new approaches to the application/architecture interface providing interdisciplinary solutions that enable new scientific advancements and/or capabilities.