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

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Abstract—Multi-stage learning is an effective technique to invoke 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 fusion block is inserted at the input of later stages to re-inject original information. The resulting multi-stage speech enhancement system, in short, multi-stage SA-TCN, is compared with state-of-the-art deep-learning speech enhancement methods using the LibriSpeech and VCTK data sets. The multi-stage SA-TCN system’s hyper-parameters are fine-tuned, and the impact of the SA block, the 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 investigated as well. 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

Speech enhancement is a basic function that is used to improve the quality and the 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 subspace algorithms based on single value decomposition and noise-estimation algorithms (see [1] and references therein). Modern techniques often use deep learning. Early examples include a recurrent neural network (RNN) to model long-term acoustic characteristics [2], and a deep auto-encoder that denoises speech signals with greedy layer-oriented pre-training [3]. In [4], a deep neural network (DNN) was used as a non-linear 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 aim to 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 research considers the use of an attention mechanism [11]–[16]. Self-attention [17] is an efficient context information aggregation mechanism that operates on the input sequence itself and can be utilized for any task that has a sequential input and output. In [15], self-attention is 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 at the same time.

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 multi-branch TCN, in short 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 in a multi-layer 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 the 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 as in each intermediate stage [28], [29], [32]. In [29], multiple stacked TCN networks are proposed for action segmentation. In [32], a multi-stage network with dynamic attention is 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 is 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 are 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 is 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 is 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 temporal convolutional network (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 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 details the proposed multi-stage SA-TCN speech enhancement system and the underlying SA, TCN, and fusion blocks. Section III details the comprehensive experiments using the 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 hyper-parameters, to determine the optimum number of stages, and to quantify the impact of the SA block and the fusion block on the performance. The use of the proposed multi-stage SA-TCN system as a front-end for automatic speech recognition (ASR) systems is investigated as well. 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 an input and aim to reconstruct 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 \( x_r(t) \) at time interval \( T_n \), i.e., \( x(t) = x_r(t \cdot T_n) \in \mathbb{R} \), and let the total number of samples be denoted by \( T \). 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

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

(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

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

(2)

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

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. For \( K \)-stage SA-TCN systems where \( K \geq 3 \), a feature fusion block is inserted prior to each stage \( k \), where \( 3 \leq k \leq K \).

Each of the blocks have special features that are particularly suited for speech enhancement. The self-attention mechanism aggregates context information across channels, which is particularly helpful in obtaining a dynamic representation when the noise is non-stationary, and this is the case for many speech enhancement scenarios.

The TCN consists of \( R \) stacks of \( L \) non-causal TCN blocks, where the dilation factor of the \( \ell \)-th TCN block in the stack is given by \( \Delta_{\ell} = 2^\ell \). As such, each stack has a large receptive field, which makes it particularly suited for temporal sequence modeling. Each TCN block has a skip connection between the input and output to reduce the loss of low-level details and to provide hooks for optimization.

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 have lost some of the speech information. A fusion block is inserted prior to each stage \( k \), where \( 3 \leq k \leq K \), that combines the predicted magnitude \( \hat{X}^{(k-1)} \) at the output of stage \( k-1 \) and the original magnitude \( X \) as input, in order to re-inject the original speech information.

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

\[
W = \frac{QK^T}{\sqrt{F}},
\]

(3)
and then use the soft-max function $\sigma(\cdot)$ to obtain $\hat{W} = \{\hat{W}_{i,j}\} = \sigma(\hat{W})$, i.e.,

$$\hat{W}_{i,j} = \exp(W_{i,j})/w_j, \quad w_j = \sum_{i=1}^{F} \exp(W_{i,j}). \quad (4)$$

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

$$A = \hat{W}V. \quad (5)$$

The SA block outputs $\hat{X} = X + \delta A$, where $\delta$ is a scalar with initial value zero that is used to allow the network to first rely on the cues in the local channels $X$ and then gradually assign more weight to the non-local channels using back-propagation to reach its optimal value.

The output $\hat{X} \in \mathbb{R}^{F\times T}$ 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 $1\times1$ convolution at its input to match the input feature dimension $B$ to the TCN block’s internal feature map dimension $H$, a dilated depth-wise 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 $1\times1$ convolution layer to reduce 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 depth-wise 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 $M^{(1)}$ that minimizes the mean absolute error loss

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

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

The stack of $L$ TCN blocks with kernel $P$ and dilation factor $\Delta_\ell = 2^{\ell-1}$ create 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 hyper-parameters $(B,H,R,L)$ will be optimized using experiments.
As indicated, the same SA-TCN structure is used for subsequent stages, and an additional element, a fusion block, is inserted prior to each stage if there are three or more stages.

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

\[
M^{(1)} = S(\Psi^{(R,L)}_1(\mathbf{T}_1(\mathbf{X}))),
\]

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

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

\[
M^{(2)} = S(\Psi^{(R,L)}_2(\mathbf{T}_2(\hat{X}^{(1)}))),
\]

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

A multi-stage SA-TCN speech enhancement system with three or more stages \( (K \geq 3) \) is constructed by inserting a fusion block that performs operation \( \Phi(\cdot) \) prior to each stage \( k \), where \( 3 \leq k \leq K \), taking the masked STFT magnitude \( \hat{X}^{(k-1)} \) and STFT magnitude \( X \) as inputs. Each input is passed through a 1x1-convolution and a PRELU operation, after which a global layer normalization (GLN) is performed \[24\]. The operation GLN(\( Y \)) is given by

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

where \( Y \in \mathbb{R}^{F \times T} \) is the input feature with mean \( E[Y] \) and variance \( \text{var}(Y) \), \( \gamma, \beta \in \mathbb{R}^{F \times 1} \) 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 1x1-convolution, a PRELU, another GLN, another 1x1-convolution and another PRELU. The output, denoted as \( \hat{X}^{(k-1)} \), is given by

\[
\hat{X}^{(k-1)} = \Phi_k \left( M^{(k-1)} \odot X, \hat{X}^{(k-1)} \right) .
\]

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

\[
M^{(k)} = S(\Psi^{(R,L)}_k(\mathbf{T}_k(\hat{X}^{(k-1)}))) .
\]

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

\[
\hat{X}^{(k)} = M^{(k)} \odot \hat{X}^{(k-1)} .
\]

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

\[
\mathcal{L}^{(k)} = \| M^{(k)} \odot \hat{X}^{(k-1)} - S \| ,
\]

where \( \hat{X}^{(k-1)} \) 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 \( \hat{X}^{(K)} \) and the original STFT phase \( \Omega \) by applying the inverse STFT, in short ISTFT, denoted as

\[
\hat{s} = \text{ISTFT}(\hat{X}^{(K)}, \Omega) .
\]

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

\[
\mathcal{L} = \sum_{k=1}^{K} \mathcal{L}^{(k)} .
\]

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 data set, model set up and the evaluation metrics are detailed.

#### A. Data Set

To verify the effectiveness of the proposed multi-stage SA-TCN system, we conduct experiments using the LibriSpeech and VCTK data sets. The detailed set-up for each data set is detailed below.

**LibriSpeech** is an open-source corpus that contains 960 hours of speech derived from audio books 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” data set. The validation set uses 800 sentences from the “dev-clean” data set, and the test set uses 500 sentences from the “test-clean” data set. The training set uses 10,000 randomly selected noise sample sequences from the DNS Challenge \[40\]. The training clean speech has been 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, . . . , 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 DEMAND 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 about 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 about 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 DARCN [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 improve 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 post-processed 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 separately. 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 the ones 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 multi-resolution STFT loss function [46], which is the sum of all STFT loss functions using different STFT parameters.

**DARCN.** DARCN [32] is a recently proposed monaural speech enhancement technique that uses multiple stages and that combines dynamic attention and recursive learning. Experiments are conducted with the open-source code using a non-causal, 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 hyper-parameters $(H, B, R, L)$. 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 mini-batch of 16 utterances. For each mini-batch 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.**

The 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 is 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. The ASR acoustic models were trained using 960 hours from the LibriSpeech training set. The word error rate (WER) was measured using the LibriSpeech “test-clean” set.

**D. Evaluation Metrics**

The 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 hyper-parameters $(H, B, R, L)$, and to analyze the effectiveness of the self-attention and fusion blocks.

The performance of 5-stage SA-TCN systems is measured in terms of PESQ and STOI scores for several hyper-parameter configurations. The results are listed in Table I. We observe that it is more effective to increase the number of channels (hyper-parameters $B$ 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 to 93.02. At the same time, 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 about 1.68 M parameters. Each SA block has about 0.2 M parameters and each fusion block has about 1.7 M parameters. If we only consider models with less 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 impact of the number of stages $K$ on the performance of a multi-stage SA-TCN speech enhancement system. The proposed multi-stage SA-TCN systems are trained using the Kaldi toolkit [49] with the standard recipe. The ASR acoustic models were trained using 960 hours from the LibriSpeech training set. The word error rate (WER) was measured using the LibriSpeech “test-clean” set.
enhancement system. The motivation for employing multi-stage learning is that the initial prediction is refined by the next stage. The results in Table I show that the performance improves step-wise after each stage. For instance, when comparing the first and the fifth stage, it 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.

### 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 | 93.40 |
| 3 | 8 | 128 | 64 | 3 | 3.59 M | 2.60 | 92.20 |
| 3 | 8 | 256 | 128 | 3 | 9.91 M | **2.73** | **93.37** |

The best score in a column is bold-faced, the second best is navy blue and the third best is dark pink.

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 a 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 that the SA block is able to aggregate the frequency context, which is helpful for TCN-based speech enhancement. 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 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. It 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 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 itself.

### 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 |

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**B. Baseline System Comparison**

Extensive experiments with the proposed multi-stage SA-TCN system and the CRN-based, complex-CNN and DARCN systems were conducted using the LibriSpeech data set. All multi-stage SA-TCN systems use hyper-parameters $(H, B, R, L) = (256, 128, 3, 8)$. 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 SA-TCN system outperforms all baseline systems in terms of PESQ score. Adding more stages improves the overall performance significantly. 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 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 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 will be 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 5-stage SA-TCN achieves an absolute improvement of 18.8%, 8.4% and 4.6% relative to CRN, complex-CNN and the DARCN methods, respectively. The ASR results are similar to the STOI performance.

D. 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. 5 shows spectrograms of the noisy speech signal, the clean speech target, as well as the 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.

E. 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 the speech enhancement metrics used in this paper. Compared with the recently proposed time-domain method DEMUSC, our proposed method uses fewer parameters and achieves better performance in terms of CBAP 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 CONCLUSIONS

In this paper, we have 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 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
further improve the performance of the proposed methods. 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.

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. The proposed methods meet this requirement and at the same time 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 a main reason for the excellent performance. The proposed multi-stage SA-TCN systems are also shown to have excellent ASR performance.

The focus of this paper is to process and enhance the speech 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. The proposed methods meet this requirement and at the same time 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 a main reason for the excellent performance. The proposed multi-stage SA-TCN systems are also shown to have excellent ASR performance.

The proposed system is process and enhance the spectrum magnitude, and the unaltered noisy phase is 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. Thus, incorporating phase information into the proposed approach may lead to further improvements. This is currently being investigated.

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**TABLE VII**

| noisyspeech | model size | feature type | PESQ | STOI | CSIG | CBAK | COVL | SI-SDR |
|-------------|------------|--------------|------|------|------|------|------|--------|
| 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 | –   |
| MHS-SKP [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 [40] (2020) | 127.9 M | Waveform | **3.07** | 0.95 | **4.31** | 3.40 | 3.63 | –   |

The best score in a column is bold-faced, the second best is navy blue and the third best is dark pink.
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