DILATED FCN: LISTENING LONGER TO HEAR BETTER

Shuyu Gong\textsuperscript{1}, Zhewei Wang\textsuperscript{1}, Tao Sun\textsuperscript{1}, Yuanhang Zhang\textsuperscript{1}, Charles D. Smith\textsuperscript{2}, Li Xu\textsuperscript{3}, Jundong Liu\textsuperscript{1}

\textsuperscript{1} School of EECS, Ohio University, Athens OH 45701  
\textsuperscript{2} Department of Neurology, University of Kentucky, Lexington KY 40506  
\textsuperscript{3} Department of Communication Disorders, Ohio University, Athens OH 45701

ABSTRACT

Deep neural network solutions have emerged as a new and powerful paradigm for speech enhancement (SE). The capabilities to capture long context and extract multi-scale patterns are crucial to design effective SE networks. Such capabilities, however, are often in conflict with the goal of maintaining compact networks to ensure good system generalization.

In this paper, we explore dilation operations and apply them to fully convolutional networks (FCNs) to address this issue. Dilations equip the networks with greatly expanded receptive fields, without increasing the number of parameters. Different strategies to fuse multi-scale dilations, as well as to install the dilation modules are explored in this work. Using Noisy VCTK and AzBio sentences datasets, we demonstrate that the proposed dilation models significantly improve over the baseline FCN and outperform the state-of-the-art SE solutions.

Index Terms— Speech enhancement, Fully convolutional network (FCN), Dilation

1. INTRODUCTION

Enhancement of audio signals in noisy environments plays an important role in many speech-related applications, such as speech recognition, hearing aids, and cochlear implants. Traditional speech enhancement (SE) techniques commonly operate on the spectral domain and rely on certain high-level features to identify target audio patterns for noise reduction. Spectral subtraction, Wiener filtering, and non-negative matrix factorization are among the operations that have been extensively studied.

In recent years, deep neural network-based models (DNNs) have emerged as a new and more powerful paradigm for many artificial intelligence (AI) related applications, including speech enhancement. Unlike traditional machine learning approaches, where certain hand-crafted features (such as fundamental frequency, formants, MFCC, etc.) need to be defined and extracted, DNN models carry out feature extraction in an automatic, data-driven fashion, greatly simplifying the system design. DNN models also facilitate a common platform for the solutions across different application areas, including computer vision and speech signal processing, to be effectively shared. Up to date, the DNN models that have been explored for speech enhancement include autoencoder (AE)\textsuperscript{1}, restricted Boltzmann machine (RBM)\textsuperscript{2}\textsuperscript{2}\textsuperscript{2}, multilayer perceptron (MLP)\textsuperscript{3}, convolutional neural networks (CNN)\textsuperscript{4}, recurrent neural networks (RNN)\textsuperscript{5}, generative adversarial network (GAN)\textsuperscript{6}, and fully convolutional networks (FCN)\textsuperscript{7}, among others.

Many of the existing SE networks operate on certain time-frequency (T-F) representation of audio signals, generated through short-time Fourier transform (STFT) on fixed-length frames. T-F representations bring great convenience to directly target on the frequency components of the audio signals. The transformations from the waveform inputs to T-F representations and back to the waveform outputs, however, impose a structural constraint to the networks, which complicates the system design and makes it difficult to predict the network performance.

FCNs on waveform provide a handy and powerful alternative. FCN models were originally developed as image segmentation solutions\textsuperscript{8},\textsuperscript{9} and have since been successfully adopted for image modality conversion, super-resolution and speech signal denoising\textsuperscript{10},\textsuperscript{11}. The fundamental goal of FCNs is to find mappings, with certain desired property, between paired signal sources; therefore they are well-suited to extracting clean waveforms out of noisy inputs\textsuperscript{12},\textsuperscript{13}. The success of FCNs, in great part, is due to their capability of processing input data from multiple spatial or temporal scales. Further improvements over the existing FCNs can be pushed forward by ensuring the models to capture longer contextual information and/or to enhance multi-scale processing. The former (longer context) can be easily achieved through the utilization of larger filters, while making the network deeper provides a solution for the latter. However, a simple combination of these two strategies will lead to a significantly increased number of parameters, which would potentially result in limited system generalization and poor performance in handling diverse noise conditions.

In this paper, we address this challenge by exploring dilated convolution operation and applying it to FCNs. Dilated convolution was originally developed for image segmentation, and its effectiveness to the task has been demonstrated in a number of works\textsuperscript{14},\textsuperscript{15}. We propose to adopt this operation to improve SE FCNs, by allowing the networks to capture longer contexts, a.k.a., “listen longer”, as well as to extract more diverse, multi-scale audio features. These features are then combined through a pyramid pooling strategy. We also explore different network locations to embed the new operations. All the improvements are made without incorporating additional layers or parameters. Using Noisy VCTK\textsuperscript{16} and AzBio sentences\textsuperscript{17} datasets, we are able to demonstrate our proposed dilated FCNs outperform the state-of-the-art solutions.

2. METHOD

Our goal is to develop an FCN addition to advance the state-of-the-art of speech enhancement. The design is based on the consideration of allowing the networks to listen longer without an increase of the number of parameters. Our efforts are focused on the explorations of 1) dilation convolutions to enlarge the receptive fields of neurons; 2) atrous spatial pyramid pooling (ASPP) module to fuse the multi-scale feature maps; and 3) different network locations in the baseline FCN to embed the ASPP modules.
2.1. Baseline FCN model

Our baseline FCN model is adopted and modified from U-Net [12], which was originally designed for segmentation of cell images. U-Net has an encoder-decoder architecture: in the encoding path, input images are processed through a number of convolution + pooling layers to generate high-level latent features, which are then progressively upsamled along the decoding path to reconstruct the target pixel labels.

To fit our data and task, we modified the original U-Net as follows. First, as the inputs and outputs of our model are one-dimensional waveforms, we replace all the two-dimensional convolution operations in U-Net with one-dimensional convolutions. We keep the original U-Net structure of two convolution layers followed by one pooling/upsampling layer. The network is made deeper to enhance its capability to capture the features in more scales. The encoding path of our modified U-Net now has 6 convolution-pooling blocks of totally 18 layers. We also use padding in convolution/deconvolution layers to maintain the spatial dimension so that the skip connections can directly concatenate encoding layers with the corresponding decoding layers. The L1 distance between network predictions (noise-reduced speech) and the ground-truth (clean speech) is used as the objective function. We term our baseline model Speech-U-Net, whose structure is shown in Fig. 1.

2.2. Dilation module

Noisy speech signals tend to contain components with diverse frequency profiles. To capture them through convolutions, filters of varying sizes would be required. Small filters work well in catching high-frequency noise, but not so effectively for low-frequency sounds. Large filters perform in an opposite way, keen to extract high-frequency noise, but not so effectively for low-frequency components. To gain long enough contextual information, one can simply add more pooling layers to make the network deeper, but that would inevitably lead to a more complicated system with an increased number of parameters, as well as longer training and inference times.

Dilated Convolution Dilated convolutions, supporting exponentially expanding RFs without the loss of resolution or coverage, can provide a remedy. Also, such expansion can be achieved without the need to increase the number of parameters. The basic idea of dilated convolution is to space out the elements to be summed in convolution by a dilation factor, as illustrated in Fig. 2. The convolutions in the bottom layer are regular 3 × 1 convolutions. The middle layer has a dilation factor of 2, so the effective RF at each neuron covers 7 audio samples. The top layer convolutions are dilated by 4, producing a 15 × 1 RF/coverage. In general, the receptive field $R_k$ of a neuron on a dilated convolution layer $l_k$ is enlarged to:

$$R_k = R_{k-1} + ((f_k - 1) \times d_k \times \prod_{i=1}^{k-1} s_i)$$  \hfill (2)

where $d_k$ is the dilation factor of layer $l_k$. Comparing with the standard version, dilated convolutions increase RFs without introducing more parameters. In addition, dilated convolutions produce exponentially expanding RFs with depth, which is in contrast to linear expansion produced by standard convolutions.

Fusion of multiscale dilations through ASPP Dilated convolutions allow us to listen longer. To extract audio patterns with great varieties, however, multiple dilation factors should be involved. Fig. 3 shows an example of applying dilated convolutions with 4 different factors. How to integrate the extracted features is a practical issue. In this work, we adopt a strategy similar to the Atrous Spatial Pyramid Pooling (ASPP) scheme proposed in DeepLab [16]. More specifically, we conduct dilated convolutions of 4 different factors in parallel and concatenate the resulted feature maps into outputs. These 4 filters are called a dilation group. Within each group, the filters have the same number of parameters (3 in the example of Fig. 3), but cover different signal ranges
because of the varying filter lengths. For an input feature map of dimension \( L \times C \), where \( L \) is the size of the map and \( C \) is the number of channels, we set the number of the dilation groups to \( C/4 \), to ensure the output feature maps to maintain the dimension of \( L \times C \). Comparing with directly utilizing \( C \) filters in the standard fashion, our dilated setup does not increase the number of parameters, but enables the network to capture longer signals with varying lengths.

![Diagram of feature map](Image)

**Figure 3:** Illustration of fusion of multiscale dilation through ASPP. Refer to text for more details.

It should be noted that dilation has been utilized in a very recent work by Tan et al. [7] in a CNN+RNN model. To the best of our knowledge, our work is the first attempt to explore dilated convolution to improve FCN models for speech enhancement.

### 2.3. Locations to add the dilation module

To exert the power of dilations + ASPP, the next step is to integrate the proposed dilation module into our baseline FCN model. To set up a proper ASPP installation, we run into two practical issues. The first question is regarding how to set the dilation factors. Our answer is based on the fact that the audio patterns to be captured in this work are mainly human phonetic symbols, whose lengths and frequencies tend to concentrate around certain ranges. It is necessary to have dilations of different ratios, but the coverages do not have to be dramatically diverging in scale. With this observation, we choose a relatively slow growing sequence, 1, 2, 3 and 4, as the dilation factors of our ASPP convolutions.

The second question is where to install the ASPP replacement. While ASPP can be installed anywhere in the network, we hope our dilated convolutions filters, even with limited number of parameters, can cover relatively long signal spans. In this regard, the end of the encoding path would be an ideal place to add ASPP, as the neurons on this layer have the largest RFs in the entire network. The further enlarged RFs by ASPP would provide a best realization of our goal of “listening longer”. This setup is illustrate in Fig. 4(a).

An alternative place to explore the ASPP replacement could be around the end of the decoding path, which consists of two convolution layers, as shown in Fig. 4(b). Replacing the first of the two layers with an ASPP would potentially allow the network to decompose the features into different scales, before they will be finally merged to face the ground-truth. Adding ASPP here would provide a (last) chance for the network to correct the integration from previous layers. With the analysis of these two choices, very naturally, another setup worth exploring would be the combination of the both. In our experiments, all three ASPP replacement schemes, as illustrated in Fig. 4 are examined.

![Diagram of feature map](Image)

**Figure 4:** Three ASPP replacement schemes: a) adding ASPP in the middle layer of the network; b) adding ASPP around the end of the decoding path; c) combination of a) and b).

### 3. EXPERIMENTS AND RESULTS

**Data sets** To evaluate the effectiveness of the proposed dilations + ASPP for speech enhancement, we conduct experiments on two groups of datasets. The first experiment is based on the Noisy VCTK dataset by Valentini et al. [17, 18], which consists of two training sets (28 and 56 speakers respectively) and a test set. We choose the 28-speaker set, in which 14 males and 14 females were recorded with around 400 sentences for each person. Noise of 10 different types, either synthetic or real, have been added to the clean speech with 4 signal-to-noise (SNR) levels (15 dB, 10 dB, 5 dB and 0 dB, respectively). Totally there are 11,571 sentences in the training set. The test dataset contains 824 sentences from two new speakers (one male and one female). Five types of noise, which are different from the 10 types in the training set, have been added. The SNR values for test set are 17.5 dB, 12.5 dB, 7.5 dB and 2.5 dB, respectively. All audio clips are sampled at 48kHz, with each time point represented as a 24-bit integer.

The second experiment was based on AzBio English sentences that were developed by Spahr et al. [19]. The dataset consisted of 33 lists with 20 sentences in each list. The sentences ranged from 3 to 12 words (median = 7) in length. All speech sentences were spoken by 2 male and 2 female adult speakers, sampled at 22,050 Hz [19]. Two types of masking noise were added to the sentences to achieve the desired SNRs (3 dB and 6 dB): speech-spectrum-shaped noise (SSN) and two talker babble (TTB).

**Preprocessing** In both experiments, we apply a preprocessing step to downsample all audio clips to 16kHz, and scale their amplitudes to [0,1]. The training set are then split randomly into training, validation and test sets with the ratio of 8:1:1. Each audio sentence is cut into multiple clips of 1 second long, which are taken as the inputs to the network. We extract the clips with a half second overlap as an approach of data augmentation. End-of-sentence clips, if short than 0.5 second, are discarded and not included as training samples.

**Evaluation metrics** Four evaluation metrics are used in this work. They are signal-to-noise ratio (SNR), segmental signal-to-noise ratio (SSNR), perceptual evaluation of speech quality (PESQ) and short-time objective intelligibility measure (STOI). SSNR calculates the average SNRs of short segments (15 to 20 ms long). PESQ evaluate the speech quality using the wide-band version recommended in ITU-T P.862.2 [20]. STOI [21] produces indicators for the average intelligibility of the degraded speech.
3.1. Results

Totally four models are evaluated in our experiments with the Noisy VCTK dataset. They are the baseline model Speech-U-Net, and three dilation models with the ASPP replacements at the middle of Speech-U-Net (bottom layer), end of the network and both locations, respectively. The evaluations were conducted on two test sets: the first one is the held-out set, which is the 10% of the training set; the other is the official test available in the dataset.

| Dataset        | Model       | SNR  | SSNR | PESQ  | STOI |
|----------------|-------------|------|------|-------|------|
| Held-out Test  | Input       | 6.040| -0.092| 1.467 | 0.838|
|                | Speech-U-Net| 14.504| 7.159| 1.849 | 0.857|
|                | ASPP-middle | 15.042| 7.718| 1.882 | 0.859|
|                | ASPP-end    | 14.389| 7.181| 1.827 | 0.873|
|                | ASPP-middle+end | 14.92 | 7.665| 1.785 | 0.877|
|                | Input       | 8.544| 1.878| 1.982 | 0.922|
|                | Speech-U-Net| 17.454| 7.955| 2.338 | 0.900|
|                | ASPP-middle | 18.418| 8.362| 2.561 | 0.902|
|                | ASPP-end    | 17.001| 8.470| 2.262 | 0.930|
|                | ASPP-middle+end | 17.529| 8.521| 2.152 | 0.938|
| Official Test  | Speech-U-Net| 2.697| -4.204| 1.062 | 0.816|
|                | ASPP-middle | 11.452| 6.958| 1.656 | 0.859|
|                | ASPP-end    | 11.734| 7.012| 1.728 | 0.874|
|                | ASPP-middle+end | 11.934| 7.124| 1.754 | 0.877|

Table 1: Experimental results on Noisy VCTK dataset

The results are shown in Table 1. It is evident that the baseline Speech-U-Net already performs rather impressively, achieving an average enhancing performance of 9 dB. Among the three dilation models, ASPP replacement at the middle (ASPP-middle) produces the best results, significantly outperforming all other competing solutions in SNR and SSNR. ASPP-end model does not help, performing even worse than the baseline model in SNR and SSNR. The combination of at-middle and at-end, unsurprisingly, has performance in-between of the two installations. Comparing the results on the held-out and official test sets, the improvements made by ASPP-middle are more significant for the latter (official test set). Considering that the official test data are acquired from new speakers with different SNRs, therefore have different data distributions than the training set, the comparison indicates that the ASPP-middle is more robust and has a better generalization capability than the baseline model. Such desired properties should be attributed to the enhanced multi-scale processing brought by the dilation operations. In other words, “listening longer” does make the network hear better. Fig. 5 shows the comparison of ASPP-middle with Speech-U-Net on a particular audio segment. Ground-truth waveforms are shown in blue, and red lines are the predictions. For the highlighted audio segment in the waveform pictures, Speech-U-Net makes rather flat predictions, failing to capture the fluctuations. Our ASPP-middle, on the other handle, makes accurate predictions for the entire segment.

For PESQ and STOI, none of the three ASPP models produces improvements over the baseline. This can be in part explained by the choice of the objective function in our models. The network updates in our models are driven to minimize the $L_1$ difference between predictions and ground-truth, which is highly related to SNR/SSNR, but does not directly involve perception and intelligibility components. To replace the $L_1$ distance with a STOI-based objective, our models are expected to produce improved performance measured by PESQ and/or STOI.

It should be noted that our ASPP-middle model also has a higher average SSNR value than the reported number from SEGAN, a state-of-the-art speech enhancement solution. While we do not intend to make a head-to-head quantitative comparison, as different experiment setups are used in the studies, the significant improvements in SSNR can nevertheless be regarded as a side evidence of the effectiveness of our ASPP-middle model. In addition, our ASPP-middle network, working as a generator, can be connected with a discriminator to make a full GAN model for further improvements.

Based on the results and observation from the VCTK experiment, we chose ASPP-middle as our proposed model. We further evaluate its capability using the AzBio sentence dataset. Speech-U-Net is still taken as the baseline model. The comparisons are shown in Table 2. Similar to the first experiment, ASPP-middle produces larger speech enhancements than the baseline, measured in SNR and SSNR. In summary, our proposed ASPP-middle approach consistently improves over the baseline, demonstrating the benefits of dilation convolutions, as well as the fusion and installation setups we designed.

| Model            | SNR  | SSNR | PESQ  | STOI |
|------------------|------|------|-------|------|
| Input            | 2.697| -4.204| 1.062 | 0.816|
| Speech-U-Net     | 9.091| -1.534| 1.334 | 0.834|
| ASPP-middle      | 9.348| -1.369| 1.315 | 0.797|

Table 2: Experimental results of Speech-U-Net and ASPP-middle on AzBio dataset

4. CONCLUSIONS

The performance of Speech-U-Net indicates that FCN is a successful architecture for waveform-based SE. The ASPP module with dilated convolution expands the RFs of the network when mounted onto a proper place of FCN. Meanwhile, it does not introduce extra parameters to the network. These advantages lead to improved achievements in both datasets we examined. We are currently working to link ASPP modules to develop FCN + RNN-based solutions for short delay and quick response, as well as to explore the integration with other deep neural networks, e.g., GAN models.
5. REFERENCES

[1] C. H. Taal, R. C. Hendriks, R. Heusdens, and J. Jensen, “An algorithm for intelligibility prediction of time–frequency weighted noisy speech,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 19, no. 7, pp. 2125–2136, 2011.

[2] Y. Wang and D. Wang, “Boosting classification based speech separation using temporal dynamics,” in Thirteenth Annual Conference of the International Speech Communication Association, 2012.

[3] ——, “Cocktail party processing via structured prediction,” in Advances in Neural Information Processing Systems, 2012, pp. 224–232.

[4] Y. Xu, J. Du, L.-R. Dai, and C.-H. Lee, “An experimental study on speech enhancement based on deep neural networks,” IEEE Signal processing letters, vol. 21, no. 1, pp. 65–68, 2014.

[5] Y. Wang, A. Narayanan, and D. Wang, “On training targets for supervised speech separation,” IEEE/ACM transactions on audio, speech, and language processing, vol. 22, no. 12, pp. 1849–1858, 2014.

[6] L. Hui, M. Cai, C. Guo, L. He, W.-Q. Zhang, and J. Liu, “Convolutional maxout neural networks for speech separation,” in 2015 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT). IEEE, 2015, pp. 24–27.

[7] K. Tan, J. Chen, and D. Wang, “Gated residual networks with dilated convolutions for monaural speech enhancement,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 27, no. 1, pp. 189–198, 2019.

[8] S. Pascual, A. Bonafonte, and J. Serrà, “Segan: Speech enhancement generative adversarial network,” arXiv preprint arXiv:1703.09452, 2017.

[9] S.-W. Fu, Y. Tsao, X. Lu, and H. Kawai, “Raw waveform-based speech enhancement by fully convolutional networks,” in 2017 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC). IEEE, 2017, pp. 006–012.

[10] S.-W. Fu, T.-W. Wang, Y. Tsao, X. Lu, and H. Kawai, “End-to-end waveform utterance enhancement for direct evaluation metrics optimization by fully convolutional neural networks,” IEEE/ACM Transactions on Audio, Speech and Language Processing (TASLP), vol. 26, no. 9, pp. 1570–1584, 2018.

[11] J. Long et al., “Fully convolutional networks for semantic segmentation,” in Proceedings of CVPR, 2015, pp. 3431–3440.

[12] O. Ronneberger, P. Fischer, and T. Brox, “U-net: Convolutional networks for biomedical image segmentation,” in MICCAI. Springer, 2015, pp. 234–241.

[13] Y. Chen, B. Shi, Z. Wang, P. Zhang, C. D. Smith, and J. Liu, “Hippocampus segmentation through multi-view ensemble convnets,” in 2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017). IEEE, 2017, pp. 192–196.

[14] Z. Wang, C. D. Smith, and J. Liu, “Ensemble of multi-sized fcns to improve white matter lesion segmentation,” in Machine Learning in Medical Imaging (MLMI 2018), Proceedings, 2018, pp. 223–232.

[15] F. Yu and V. Koltun, “Multi-scale context aggregation by dilated convolutions,” in International Conference on Learning Representations, 2016.

[16] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, “Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs,” IEEE transactions on pattern analysis and machine intelligence, vol. 40, no. 4, pp. 834–848, 2018.

[17] C. Valenti-Botinhao, X. Wang, S. Takaki, and J. Yamagishi, “Investigating rnn-based speech enhancement methods for noise-robust text-to-speech,” in ISW, 2016, pp. 146–152.

[18] C. Valenti-Botinhao et al., “Noisy speech database for training speech enhancement algorithms and tts models,” University of Edinburgh. School of Informatics. Centre for Speech Technology Research (CSTR), 2017.

[19] A. J. Spahr, M. F. Dorman, L. M. Litvak, S. Van Wie, R. H. Gifford, P. C. Loizou, L. M. Loisel, T. Oakes, and S. Cook, “Development and validation of the azbio sentence lists,” Ear and hearing, vol. 33, no. 1, p. 112, 2012.

[20] I. Rec, “P. 862.2: Wideband extension to recommendation p. 862 for the assessment of wideband telephone networks and speech codecs,” International Telecommunication Union, CH–Geneva, 2005.

[21] C. H. Taal, R. C. Hendriks, R. Heusdens, and J. Jensen, “A short-time objective intelligibility measure for time-frequency weighted noisy speech,” in 2010 IEEE International Conference on Acoustics, Speech and Signal Processing. IEEE, 2010, pp. 4214–4217.

[22] Y. Chen, B. Shi, Z. Wang, T. Sun, C. D. Smith, and J. Liu, “Accurate and consistent hippocampus segmentation through convolutional lstm and view ensemble,” in International Workshop on Machine Learning in Medical Imaging. Springer, 2017, pp. 88–96.

[23] Z. Wang, W. Cai, C. D. Smith, N. Kantake, T. J. Rosol, and J. Liu, “Residual pyramid fcn for robust follicle segmentation,” in 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019). IEEE, 2019, pp. 463–467.