Towards End-to-End Speech Enhancement with a Variational U-Net Architecture

Eike J. Nustede and Jörn Anemüller

Computational Audition Group
Dept. med. Physics & Acoustics and Cluster of Excellence Hearing4all
Carl von Ossietzky Universität Oldenburg
Oldenburg, Germany

Abstract
In this paper, we investigate the viability of a variational U-Net architecture for denoising of single-channel audio data. Deep network speech enhancement systems commonly aim to estimate filter masks, or opt to skip preprocessing steps to directly work on the waveform signal, potentially neglecting relationships across higher dimensional spectro-temporal features. We study the adoption of a probabilistic bottleneck, as well as dilated convolutions, into the classic U-Net architecture. Evaluation of a number of network variants is carried out using signal-to-distortion ratio and perceptual model scores, with audio data including known and unknown noise types as well as reverberation. Our experiments show that the residual (skip) connections in the proposed system are required for successful end-to-end signal enhancement, i.e., without filter mask estimation. Further, they indicate a slight advantage of the variational U-Net architecture over its non-variational version in terms of signal enhancement performance under reverberant conditions. Specifically, PESQ scores show increases of 0.28 and 0.49 in reverberant and non-reverberant scenes, respectively. Anecdotal evidence points to improved suppression of impulsive noise sources with the variational end-to-end U-Net compared to the recurrent mask estimation network baseline.

Index Terms—Speech enhancement, U-Net architecture, variational autoencoder, deep learning, audio source separation

1. Introduction
In real-world environments, where speech is inevitably distorted by background noise, reverberation or other speakers, speech intelligibility degrades and applications such as automatic speech recognition (ASR) and speaker identification (SID) perform poorly [1,2]. Speech Enhancement is used in speech-related applications to improve the signal to noise ratio (SNR), thus increasing speech quality. Deep learning approaches commonly follow two approaches: generating filter masks or directly mapping the noisy mixture to enhanced speech. Different types of mask-based methods have been used in the literature, such as ideal binary masks (IBM) and ideal ratio masks (IRM) [3]. Auto-encoder based approaches to speech enhancement favor compact features such as Mel-frequency power spectra [4] and short term Fourier transform (STFT) spectra computed across short utterances [5,6,7] or a small temporal context [8]. Deep networks predominantly use higher-dimension log-power spectra with a comparably long temporal context in an attempt to learn features best representing clean speech [9,10]. Recent works focus on using DNNs to generate ideal filter masks based on these self-learned speech representations [11,12], where each mask corresponds to one target speaker. Psycho-acoustic modeling is combined with a speech quality optimization target in [13]. End-to-end systems for sound source separation [14] have been adopted for speech denoising, e.g., WaveNet [15]. The present work’s main contribution is to propose and study the viability of a variational U-Net architecture, which, to the best of our knowledge, has not been used for speech enhancement previously. We hypothesize that the inclusion of a variational bottleneck into the U-Net architecture increases robustness towards out-of-distribution effects, such as unknown noise types or reverberation. We investigate the performance of the proposed model, as well as of several systems with ablations.

2. Proposed System

2.1. U-Net Architecture
The U-Net architecture [16], originally proposed for biomedical signal processing, has recently been used for audio source separation tasks [14,17,18]. More importantly, it has also been adapted for speech enhancement [11] with the addition of dilated convolutions. It has been shown that the generation of filter masks with a dilated U-Net performed better than without dilation, indicating the usefulness of dilation in...
such a network. In computer vision, the U-Net architecture was combined with the probabilistic modeling found in variational auto-encoders (VAE) [19][20]. Supervised systems tend to struggle with unknown interference, i.e., unknown noise types or reverberation. Therefore, we propose to unite the dilated U-Net with a VAE approach to leverage the benefits of both. Specifically, the additional information contained in U-Net’s residual connections, the inter-frequency and time relations found by dilated convolutions and the robustness towards out of distribution effects of a VAE. By moving in a modular fashion from the standard VAE to the proposed system (cf. Fig. 1), we are able to study the impact each step has w.r.t. perceived sound quality.

2.2. Proposed Network Description

The general operations in the encoder and decoder are the same for all models. The encoder blocks include two convolution layers with 3-by-3 kernels, followed by batch normalization and parametric ReLU activation, noted as "Down" in Fig. 1. A copy of a block’s output is given to the corresponding decoder, while a max-pooling is applied to the original output before going into the next block. If dilation is used, the blocks only use one 3-by-3 dilated convolution instead of two. The first \(N+1/2\) blocks increase the number of feature maps, whereas the leftover blocks use depthwise separable convolutions\([21]\) instead. They retain the same number of feature maps while further reducing the total dimensionality, similar to the approach in \([19]\). In the bottleneck (Fig. 2), a 1-by-1 convolution linearly transforms the encoded features, which is not necessary for the baseline U-Net but does improve training stability on our variational models. The decoder blocks include transposed convolutions, self-learning upsampling operations, with 2-by-2 kernels and a stride of 2. Before each upsampling, the residuals from the encoder are concatenated to the input of a decoder block along the feature ("channel") axis.

2.3. Loss Function

We use the mean-squared error (MSE) as our primary reconstruction loss. Kullback-Leibler Divergence is used in addition to the MSE for our probabilistic models. In the spectral domain, input signal \(X(k)\), which includes speech \(X_s(k)\) and noise \(X_n(k)\) components, is given by

\[
X(k) = X_s(k) + X_n(k).
\]  

Let \(S(k)\), \(S_s(k)\) and \(S_n(k)\) denote respective log-power spectra, with \(S(k)\) being the input feature for our model and \(S_s(k)\) the training target. The MSE is expressed as

\[
L_{MSE} = E[||S_s(k) - Y(k)||^2]
\]  

where \(Y(k)\) denotes the enhanced spectrum at the output of the network. The KL-Divergence term \(D_{KL}(Q(z|S)||P(z))\)
minimizes the distance between the latent space encoding $z$ computed by the encoding (downsampling) path $Q(z|S)$ of the model, and the decoding (upsampling) path estimates the generative model $P(Y|z)$ under a Gaussian prior $P(z)$ assumption. The total loss is given by

$$L = L_{\text{MSE}} + w_{KL} \cdot D_{KL}(Q(z|S)\|P(z)), \quad (3)$$

with $w_{KL}$ balancing reconstruction loss and KL-divergence.

### 3. EXPERIMENTS

#### 3.1. Dataset Configuration

Our datasets are generated with the scripts and data provided by the MS-SNSD dataset [22]. The speech, i.e., clean audio, is normalized on a per utterance basis, while the noise is scaled to have one SNR in a range of 0 to 20 dB SNR for a total of 21 different SNRs. Each SNR level is present at least once. The speech and noise files are randomly selected and mixed to create noisy utterances. All audio files are 30 seconds long and sampled at 16 kHz. We extract the log-scaled power spectra with a 1024-point STFT with a Hann window of 25 ms length and a hop length of 6.25 ms as our feature representations. Training sets of different sizes (1 hour, 15 hours, and 100 hours), a validation set of 2 hours, and a test set of 10 hours of audio data are utilized in our setup. The 10-hour test set is the same for all experiments. Additionally, a 25-minute long test set is studied with and without reverberation, which was pre-mixed in the MS-SNSD dataset.

### Table 1. Performance (SI-SDR) in dependence on training set length and model characteristics (V: variational, U: U-Net, D: dilated convolutions). Identical 10h test set in all conditions.

| Algorithm    | 10h test SI-SDR [dB] | training duration |
|--------------|----------------------|-------------------|
| Model        |                      | 1h     | 15h     | 100h    |
| DVUNET       | V+U+D 134 M          | 14.48  | 15.90   | 16.68   |
| DUNET        | U+D 133 M           | 14.46  | 15.99   | 16.70   |
|UNET          | U 146 M            | 14.75  | 16.08   | 16.51   |
|DV AE         | V+D 44 M           | 7.92   | 8.69    | 8.84    |
|VAE           | V 56 M            | 8.28   | 9.16    | 9.20    |
|AE            | ./. 56 M          | 9.63   | 12.77   | 13.25   |
|Input data    | 9.98                |        |         |         |
|Baseline NSNet| 10.52               |        |         |         |

#### 3.2. Training and Evaluation

The input and output of each network is a subset of the log-power spectral frames representing 3.2–seconds. Training is done for a maximum of 200 epochs, with early stopping criteria for 10 validation epochs. Validation is performed multiple times during one epoch (twice for 15-hour data, ten times for 100-hour data). The 1–hour sets use a static learning rate of 0.001 with a single validation run at the end of each epoch. Adam optimizer is used with a learning rate warm-up for the first 500 batches of the 15–hour and 100–hour training sets. Adding dilation to the UNET and VAE is noted as “DUNET” and “DVAE.” Adding a variational bottleneck to the DUNET
is then called "DVUNET," which is our proposed system. Every model consists of the same operations otherwise. We evaluate the performance when trained on varying training set lengths. The 1-hour results are averaged across 10 different models trained on 10 different sets. We measure the scale-invariant signal to distortion ratio (SI-SDR) [23] and compare our results to the baseline model associated with the MS-SNSD dataset [8]. The SI-SDR is calculated directly on the 3.2-second output spectra. Note that the baseline was only available as a pre-trained model. The baseline was trained on five different SNRs (40, 30, 20, 10, and 0 dB), while our data, as described above, includes 21 different SNRs from 0 to 20 dB, which induces a stronger weighting to frequently encountered moderately adverse scenarios. Otherwise, the training conditions are equal to our setup. To assess the reverberant/non-reverberant test set, we turn to the perceptual evaluation of speech quality (PESQ) and Short-Time-Objective-Intelligibility (STOI) metrics instead. Reconstruction of the waveform is done with the phase of the noisy signal.

4. RESULTS & DISCUSSION

We want to study the impact of different additions to the U-Net architecture concerning perceived speech quality. First, we compare the performance of all models on our 10-hour long test set. SDR values reported in Tab. 1 are calculated on spectrogram frames instead of the time-domain waveform since they directly represent our input and output. For the SDR, every model performs better when trained on larger datasets. The VAE and DVAE models decrease SDR, where U-Nets showed consistent improvements. This leads us to believe that the residual connections present here contribute significantly to the task. The impact of the probabilistic bottleneck seems negligible, if not detrimental. The standard autoencoder performed notably better than its variational counterparts. We also observe that model the U-Net architecture performs best out of all models on the small datasets but is outperformed by DVUNET and DUNET trained on the 100-hour set. Since the difference between the two latter models is negligible, we assume the dilation to be the deciding factor for this effect. In the perceptual evaluation (cf. Tab. 2), we observe a marginally higher PESQ on the standard UNET than dilated versions without reverberation. With reverb, however, the UNET degrades to a PESQ of 1.60, whereas the DUNET shows a PESQ of 2.28, and the proposed DVUNET performs even better at 2.44. Contrary to expectation, when trained on 100-hours, the DVUNET and DUNET perform worse, while the UNET, AE, and DVAE roughly stay the same. This might indicate some form of overfitting regarding the features learned across time and frequency due to dilation. Nonetheless, the differences between DUNET and DVUNET in both cases lead us to believe that the variational bottleneck does improve robustness. Overall, dilation and probabilistic bottleneck seem advantageous regarding speech quality on data with reverberation while showing no to minimal improvement on data without it.

5. CONCLUSION

The present contribution developed an end-to-end speech enhancement system based on the U-Net architecture for which we introduced a variational bottleneck. Model training was performed for several ablation models on training data of different lengths, with evaluation on test data that included unknown noise sources and reverberation. Experiments showed that residual U-Net connections are strictly necessary for efficacious speech enhancement. We hypothesize that they possess relevance for learned speech representations in general. The proposed model, which combines dilated convolutions, variational bottleneck, and residual connections, performed well on data with reverberation, a fact that supports our initial motivation to increase robustness against common variability of acoustic parameters. Future work will aim to further optimize the proposed architecture for end-to-end speech enhancement.
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