UX-NET: FILTER-AND-PROCESS-BASED IMPROVED U-NET FOR REAL-TIME
TIME-DOMAIN AUDIO SEPARATION

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ABSTRACT

This study presents UX-Net, a time-domain audio separation network (TasNet) based on a modified U-Net architecture. The proposed UX-Net works in real-time and handles either single or multi-microphone input. Inspired by the filter-and-process-based human auditory behavior, the proposed system introduces novel mixer and separation modules, which result in cost and memory efficient modeling of speech sources. The mixer module combines encoded input in a latent feature space and outputs a desired number of output streams. Then, in the separation module, a modified U-Net (UX) block is applied. The UX block first filters the encoded input at various resolutions followed by aggregating the filtered information and applying recurrent processing to estimate masks of separated sources. The letter ‘X’ in UX-Net is a name placeholder for the type of recurrent layer employed in the UX block. Empirical findings on the WSJ0-2mix benchmark dataset show that one of the UX-NET configurations outperforms the state-of-the-art Conv-TasNet system by 0.85 dB SI-SNR while using only 16% of the model parameters, 58% fewer computations, and maintaining low latency.

Index Terms— Speech separation, multi-channel processing, neural networks, recurrent networks, real-time processing

1. INTRODUCTION

Hands-free voice-assisted technologies have seen tremendous growth in recent years. Speech-to-text services, smart home assistants, and automatic meeting diarization are just a few examples. However, susceptibility to errors in multi-talker scenarios is a well-known limitation of these technologies. Solutions include: extracting the speech of the targeted speaker [1] (Speaker Extraction) and separating all overlapping speech from the mixture [2] (Speech Separation) followed by attending to the information separately. Speech separation is a speaker-independent and more generic technique that piqued academic curiosity. Recent developments in deep learning models have significantly improved the performance of state-of-the-art (SOTA) speech separation models [3, 4] on various benchmark datasets. Deep learning-based (DL) solutions are known to be computationally and memory demanding. However, speech processing applications are often constrained to run in real-time and be energy-efficient. Therefore, this paper offers a deep learning architecture for real-time (causal) speech separation, for either single or multi-channel input, that is both computationally and memory efficient.

The time-domain audio separation network (TasNet) is a significant class among the best-performing DL systems. TasNet follows an encoder-decoder-based structure which transforms the time domain signal into a latent space, analogous to the short-time Fourier transform (STFT) domain, where it estimates masks of the sources followed by reconstruction of the separated signals into the time domain. In TasNet, permutation invariant training [5] (PIT) is employed to solve the permutation problem. The initially proposed non-causal bi-directional long-short term memory [6] (Bi-LSTM) based TasNet was shown to outperform STFT-based DL approaches [4]. Separation was then improved with the dilation-based temporal convolution network (TCN) in Conv-TasNet [7]. The results of Conv-TasNet suggested that long-term sequential context awareness is needed to process auditory information effectively. As a result, dual-path data segmentation-based neural networks, such as the Dual-path Recurrent Neural Network [8] (DPRNN), the Dual-path Transformer Neural Network [9] (DPTNN), and the Globally Attentive Locally Recurrent [10] (GALR) network, were proposed to further improve separation by processing both local and global contexts. Inspired by the success in image segmentation, U-Net [11] based architectures, such as Wave-U-Net [12] and Sudo Rm-Rf [13], also became popular among TasNet-like systems. In a U-Net, a signal is repeatedly downsampled and upsampled with skip connections at different resolutions to provide extended context aggregation.

In real-time or causal speech separation, speech is separated using only current and past data. Few causal speech separation architectures have been proposed in the literature. Tweaking Conv-TasNet into a causal configuration resulted in significant performance deterioration when compared to its non-causal counterpart. The dilated temporal convolutions in Conv-TasNet keep the local and global context-aware DPRNN, DPTNN, and GALR models are unsuitable for causal processing. Similarly, the U-Net-based architectures Wave-U-Net and Sudo Rm-Rf perform resampling in the time axis, making them inherently non-causal. Inspired by research in computational auditory scene analysis (CASA), the causal Deep CASA [14] presented a U-Net-based clustering algorithm for causal speech separation in the frequency domain. Although Deep CASA attains high separation performance, it incurs excessive latency when compared to TasNet-like systems.

Motivated by the above observations, we revise the U-Net architecture and TasNet structure for low-cost, low-latency causal speech separation. As a result, we offer UX-Net. The human brain processes mixed sound at several resolutions and contexts, first masking out undesired noises, i.e., filtering, then aggregating the information, and finally processing the individual sounds in
parallel [15, 16]. Inspired by this filter-and-process technique, our system introduces novel cost and memory efficient mixer and separation modules. In the mixer module, the encoded, either single or multi-channel input is mixed and mapped into a desired number of output streams. In the separation module, the mixer output is processed by a modified U-Net (UX) block. The initial half of the UX block filters the encoded input at various resolutions using convolutional neural network (CNN) units. The second half of the UX block employs a set of CNN and recurrent neural network (RNN) units to aggregate and process the filtered input at the different resolutions. In contrast to a typical U-Net, resampling is performed solely across the feature dimension to ensure causality. CNNs have a local receptive field and are excellent at filtering, while RNNs with gated capabilities, such as LSTM or Gated Recurrent Units (GRUs), provide an adaptive receptive field and longer context window without explicitly retaining long data history. Thus, the combination of both is used in UX-Net to improve upon the classical design of a U-Net. The letter ‘X’ in UX-Net is a name placeholder for the type of RNN employed.

UX-Net is benchmarked against SOTA causal speech separation methods using the WSJ0-2mix dataset. Results show that the proposed system is capable of achieving very high separation performance; (2) ensuring scalable model size for varying channel dimension, resulting in the 3-dimensional (3D) tensor $X \in \mathbb{R}^{M \times K \times L}$. Given $X$, the task is then to estimate the tensor $S \in \mathbb{R}^{C \times K \times L}$ representing the corresponding extracted frames of the $C$ speech sources.

3. SEPARATION SYSTEM

As shown in Fig. 1, the proposed separation system consists of encoder, mixer, separation, and decoder modules.

3.1. Encoder

The encoder begins by cumulatively normalizing the raw time-domain input $X$, which is then sent through a feed-forward layer $F_e$ having weights $W_e \in \mathbb{R}^{L \times N}$ and no bias. Thus, analogous to the STFT, $F_e$ transforms each time-domain frame into its representation in a latent-space using the $N$ basis signals in $W_e$. The complete encoder operation is given by

$$E = \text{ReLU}(F_e(cLN(X)))$$

where $\text{ReLU}()$ is the rectified linear unit and $cLN()$ denotes cumulative normalization [7]. The tensor $E \in \mathbb{R}^{M \times K \times N}$ represents the weights of the normalized input mixture in a latent space. ReLU is used here to ensure non-negative weights.

3.2. Mixer

In the mixer module, the $M$-channel encoded input $E$ is mapped onto a $C$-channel tensor by convolution across the time and feature axes followed by combination across the channel axis. As such, this module has two purposes: (1) learning spatial features for improved separation performance; (2) ensuring scalable model size for varying number of input channels. The mixer operation is given by

$$E_M = \text{PReLU}(cLN(Conv2D(M_1,M_2,3,3)(E)))$$
$$E_C = \text{PReLU}(cLN(Conv2D(M_1,M_2,3,3)(E_M)))$$

where $Conv2D(M_1,M_2,3,3)$ is a 2D $3 \times 3$ convolutional layer with $M_1$ and $M_2$ being the respective number of input and output channels, $\text{PReLU}()$ denotes parametric ReLU [17]. $E_M \in \mathbb{R}^{M \times K \times N}$ and $E_C \in \mathbb{R}^{C \times K \times N}$ are respective intermediate and final outputs of the mixer. In all convolutional layers of UX-Net, the input is zero-padded from the left to ensure matching output size while preserving causality.

3.3. Separation

Given $E_C$ in (6) as input, the separation module estimates the masks of each source with respect to the first channel of $E$ in (5). Separation (in a latent space) is then achieved by

$$E^{(i)}_S = E^{(i)}_{mask} \odot E^{(i)}_C, \quad i \in \{1, \ldots, C\}$$

where $E^{(i)}_S \in \mathbb{R}^{1 \times K \times N}$ is the first channel of $E$, the $\odot$ denotes the Hadamard product, $E^{(i)}_{mask} \in \mathbb{R}^{1 \times K \times N}$ is the $i$-th channel of the
is given by $L$ feature dimension by a factor of two and fed as input to the next (CI). Then, the output of the depth-wise (DW) convolution [18], which avoids channel interaction output of an $L_B$ of shared weights, resulting in fewer parameters to train. The output the different channels limits computational complexity and enables applied in parallel across each channel. Parallel processing across and feed-forward layers. The recurrent and feed-forward layers are multi-channel input using a sequence of convolutional, recurrent, $B$, feature resolution. Both $L_B$ and channel input onto $C$-channel output, whereas $R$-channel input onto $C$-channel output. Depending upon the type of recurrent processing applied in the $B$ and $R$ units, UX-Net is renamed to either UL-Net, if LSTMs are used, or UG-Net, if GRU layers are used.

The architecture of the proposed UX block is largely inspired by the filter-and-process-based human auditory behavior. Compared to the classical U-Net design, a UX block introduces three key differences: (1) resampling is performed across the feature axis instead of the time axis, thus preserving causality; (2) recurrent layers are introduced for global context awareness; (3) channel dimensionality is fixed instead of being doubled as resolution decreases, limiting the overhead of depth on the model complexity.

3.4. Decoder

The decoder transforms the extracted sources in the latent space to the corresponding time domain signals. First, $E_S$ is mapped onto $\mathbf{S}$ by a feed forward layer $F_d$ with weights $W_d \in \mathbb{R}^{N \times L}$ as given by

$$\mathbf{S} = F_d(E_S). \quad (9)$$

Then, the overlap-add method is applied on the $C$ channels of $\mathbf{S}$ to extract the final separated waveforms.

4. EXPERIMENTS

4.1. Datasets

We conduct speech separation experiments using two popular datasets: Wall Street Journal (WSJ) [19] and LibriSpeech [20].

Dataset 1: We consider the WSJ0-2mix [6, 21, 22] two-speaker speech mixture dataset derived from WSJ. WSJ0-2mix is used for benchmarking UX-Net against different SOTA causal speech separation models. This dataset, however, has two limitations: (1) mixtures consist of close-talk speech lacking reverberant components; (2) only mixtures with 100% overlap are considered, which are rare in practice.

Dataset 2: Aiming to overcome the limitations of WSJ0-2mix, we use clean speech utterances from LibriSpeech and generate a dataset simulating two overlapping speech sources captured by a microphone array in a reverberant room. This dataset contains 30 h training, 5 h validation, and 5 h test sets consisting of 4-second-long utterances. The signals are sampled at 8 kHz. For each utterance, the dimensions of the room are randomly sampled between 5 and 10 meters in length and width, and 2 to 5 meters in height. The reverberation time ranges randomly between 0.1 and 0.5 seconds. The speech overlap ratio and the signal-to-interference ratio (SIR) vary randomly between 5% and 95% and 0 and 5 dB, respectively. Speech sources are distributed randomly around the room with the constraint of being at least 50 cm away from the walls. The microphone array consists of a 5-element circular array with a radius of 5 cm. The microphone array is placed in the middle of the room and the image method [23] is applied to generate the corresponding room impulse responses (RIRs). The training target utterances include up to 50 ms of reverberation following the direct path [24], emphasizing separation and dereverberation as per (4).

4.2. Training and Evaluation

Training loss is given by the negative of scale-invariant SNR (SI-SNR) averaged across the separated sources in a mixture. SI-SNR [25] measures the scale-invariant similarity between a target signal $s$ and an estimated signal $\hat{s}$. It is given by

$$SI\text{-SNR} := 10 \log_{10} \left( \frac{\|s\|^2}{\|s - \alpha \hat{s}\|^2} \right), \quad (10)$$

where $\alpha = \frac{\hat{s}^T s}{\|s\|^2}$ is the scalar projection of $s$ onto $\hat{s}$. PIT training with Hungarian algorithm [26] is employed to solve the permutation
problem. The network is trained for 100 epochs with Adam [27] optimizer and a batch size of 4. The initial learning rate is set to $10^{-3}$ and later multiplied by 0.98 every two epochs. Gradients are clipped to $([-5, 5])$ during the backward pass to avoid the exploding gradient problem. The models with best validation loss are saved and evaluation results are reported on the test sets. Consistent with other TasNet systems, we found that best performance is achieved using a small frame size. Thus, a frame size of 2 ms with 1 ms (50%) overlap is used, resulting in a total algorithmic latency of only 3 ms when allowing 1 ms of processing time per frame.

The performance metrics used are: improvement in SI-SNR (SI-SNRi), Perceptual Evaluation of Speech Quality [28] (PESQ), and Short-Time Objective Intelligibility [29] (STOI).

### Table 1. Comparison with causal SOTA on WSJ0-2mix dataset.

| Model         | Params. (M) | GMAC/s | SI-SNRi (dB) /PESQ/STOI |
|---------------|-------------|--------|--------------------------|
| LSTM-TasNet   | 32.00       | 12.80  | 10.80/7.21/0.87          |
| Conv-TasNet   | 5.05        | 5.23   | 10.60/7.21/0.87          |
| Deep-CASA\(^\circ\) [14] | 12.80       | -      | 15.20/3.25/0.90          |
| UG-Net \((N = 128)\) | 0.16        | 0.47   | 9.73/2.71/0.87           |
| UG-Net \((N = 256)\) | 0.63        | 1.82   | 11.13/2.82/0.88          |
| UL-Net \((N = 128)\) | 0.20        | 0.56   | 10.18/2.78/0.87          |
| UL-Net \((N = 256)\) | 0.80        | 2.17   | 11.45/2.92/0.89          |
| UL-Net 2x \((N = 256)\) | 1.59        | 4.32   | 12.41/3.01/0.90          |
| UL-Net 4x \((N = 256)\) | 3.17        | 8.63   | 13.60/3.12/0.90          |

\(^\circ\) Frequency domain method with a frame size of 32 ms.

### 4.3. Results

In the first experiment, we employ the WSJ0-2mix benchmark dataset to perform single-channel speech separation as defined in (3). Table 1 compares the performance of UX-Net to the SOTA causal frequency-domain LSTM-TasNet and Conv-TasNet, as well as the causal frequency-domain Deep CASA. Different configurations of UX-Net are considered by varying the recurrent layer used (either LSTM or GRU) and the latent space dimensionality \(N\). We also evaluate the effect of deepening the separation module of UX-Net with multiple successive UX blocks with skip connections. The \(n\) in UX-Net \(n\)x denotes the number of repeated UX blocks. The depth \(D\) is set to 5 in all UX-Net configurations. For the SOTA methods, only the best reported results are listed, and the unreported fields are left blank. The field GMAC/s specifies a model’s number of Giga Multiply-Accumulate operations per second during inference. The results show that UX-Net can outperform both LSTM-TasNet and Conv-TasNet while incurring significantly lower computational and memory cost. In fact, the LSTM-based configuration with \(N = 256\) outperforms Conv-TasNet by 0.85 dB SI-SNRi while needing only 16% of the model parameters and 58% fewer computations. Deep-CASA attains the best performance, but not without incurring somewhat excessive system latency common to frequency-domain models. Separation performance of UX-Net is shown to improve as the number of UX blocks increases.

In the second experiment, we employ the generated multi-channel LibriSpeech dataset to perform speech separation with dereverberation as defined in (4). Table 2 compares the performance of UX-Net to Conv-TasNet. By default, the number of input channels is one unless otherwise specified. In all UX-Net configurations, we let \(D = 5\) and \(N = 256\). For Conv-TasNet, we used the author’s best-performing implementation and trained it with the generated dataset under the same conditions as UX-Net. It is confirmed once more that the proposed system outperforms Conv-TasNet. Moreover, we notice that the performance of UX-Net improves for an increased number of input channels without a significant effect on computational and memory complexities.

In the third experiment, we conduct an ablation study of UX-Net to verify the effectiveness of increased depth, no CI in \(L\) units, and use of cLN. Table 3 reports the results. RTF gives the real-time factor of an AMD Ryzen 7 3800X CPU when processing one second of input data using a specified model configuration. We see that increasing the depth improves performance without significant effect on RTF. In contrast to a typical U-Net, little effect on RTF is attributed to the fact that as depth increases, the number of additional parameters needed in UX-Net decreases exponentially. We also notice that when CI is allowed by substituting the depth-wise convolution in an \(L\) unit with regular convolution, SI-SNRi drops by 0.11 dB. Furthermore, replacing cLN with framewise normalization lowers SI-SNRi by 0.54 dB. Finally, low RTF values confirm the real-time feasibility of UX-Net.

### Table 2. Analysis on reverberant multi-channel LibriSpeech dataset.

| Model         | Params. (M) | GMAC/s | SI-SNRi (dB) /PESQ/STOI |
|---------------|-------------|--------|--------------------------|
| Conv-TasNet   | 5.05        | 5.23   | 6.5/2.15/0.75            |
| UL-Net        | 0.80        | 2.17   | 7.35/2.27/0.79           |
| UG-Net        | 0.63        | 1.82   | 7.17/2.21/0.77           |
| UG-Net (3-Channel) | 0.69    | 1.86   | 7.89/2.31/0.81           |
| UG-Net (5-Channel) | 0.72    | 1.94   | 8.51/2.43/0.83           |

### Table 3. Ablation study.

| Model         | \(D\) | SI-SNRi (dB) /PESQ/STOI | RTF     |
|---------------|------|--------------------------|---------|
| Conv-TasNet   | 3    | 6.5/2.09/0.70            | 0.11    |
| UL-Net        | 4    | 6.96/2.17/0.73           | 0.13    |
| UG-Net \((N = 256)\) | 5    | 7.17/2.21/0.77           | 0.14    |
| UG-Net \((N = 256)\) | 5    | 7.06/2.19/0.76           | 0.15    |
| UG-Net \((N = 256)\) | 5    | 6.63/2.11/0.71           | 0.11    |

5. CONCLUSION

This study presented a time-domain architecture for either single or multi-channel causal speech separation. Two novel mixer and separation modules were introduced to the TasNet system. The mixer module limits the model complexity while providing improved performance for increasing number of input channels. The separation module estimates masks of the different sources in a latent space employing a causal U-Net-like architecture inspired by the filter-and-process-based human auditory behavior. Experiments showed that using a single UX block in the separation module our system outperforms SOTA on time domain, causal speech separation while incurring lower computational and memory cost. Further increase in performance was observed when deepening the separation module with multiple successive UX blocks.
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