A TIME-DOMAIN GENERALIZED WIENER FILTER FOR MULTI-CHANNEL SPEECH SEPARATION

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ABSTRACT

Frequency-domain neural beamformers are the mainstream methods for recent multi-channel speech separation models. Despite their well-defined behaviors and the effectiveness, such frequency-domain beamformers still have the limitations of a bounded oracle performance and the difficulties of designing proper networks for the complex-valued operations. In this paper, we propose a time-domain generalized Wiener filter (TD-GWF), an extension to the conventional frequency-domain beamformers that has higher oracle performance and only involves real-valued operations. We also provide discussions on how TD-GWF can be connected to conventional frequency-domain beamformers. Experiment results show that a significant performance improvement can be achieved by replacing frequency-domain beamformers by the TD-GWF in the recently proposed sequential neural beamforming pipelines.

Index Terms: Speech separation, Wiener filter, Neural network

1. INTRODUCTION

Recent studies on neural beamformers have significantly advanced the state-of-the-art of multi-channel speech enhancement and separation systems [1][2]. A neural beamformer typically first applies a neural network to extract the target sources in the noisy observations and then uses a conventional beamformer to perform spatial filtering. Despite a few studies that explored the effect of time-domain beamformers [3], frequency-domain beamformers such as the multi-channel Wiener filter (MCWF) and the minimum-variance distortionless response (MVDR) beamformers are the default choices since both the microphone array and target source characteristics can be estimated in the frequency domain in a much easier way.

Prior works on time-domain single-channel speech separation have discussed the potential drawbacks for conventional time-frequency (T-F) masking [4]. Similarly, there are also two core limitations of the conventional frequency-domain neural beamformers: the upper-bound performance and the complex-valued operations. On the one hand, the performance of neural beamformers are upper-bounded by their performance when the oracle target sources are used for the calculation of source-specific features such as the spatial covariance matrices, and the neural beamformers can fail when the upper-bound performance of the selected beamformer is bad. On the other hand, with more and more recent works started to apply neural networks on complex-valued spectrograms, how to properly handle the real and imaginary parts of the features in the nonlinear transforms becomes an important problem. Although a common way is to concatenate the real and imaginary parts into a single vector, how to effectively incorporate nonlinear complex-valued operations to the neural beamformers is still a topic to discuss.

In this paper, we propose a simple time-domain generalized Wiener filter (TD-GWF) as an alternative to frequency-domain conventional beamformers for multi-channel speech separation. TD-GWF directly performs minimum mean-square error (MMSE) estimation on the full waveforms without the need for a signal transformation such as short-time Fourier transform (STFT). As a result, all operations in TD-GWF are real-valued and any existing neural network blocks can be easily used together with it. Moreover, TD-GWF introduces more degrees of freedom in the optimization problem to be solved and significantly improves the oracle performance with respect to common signal quality metrics. With certain hyperparameter configurations, we also show that conventional beamformers are special cases of the TD-GWF. For neural beamformers, we apply TD-GWF in the recently proposed sequential neural beamforming pipeline, where multiple iterations of separation and beamforming operations are utilized to gradually improve the overall performance [14][15]. Experiment results show that the oracle performance of TD-GWF is significantly higher than that of frequency-domain MCWF, and replacing the frequency-domain MCWF by TD-GWF in the sequential neural beamforming pipeline drastically improves the separation performance.

The rest of the paper is organized as follows. Section 2 briefly overviews the conventional filter-and-sum beamformers and introduces the proposed TD-GWF. Section 3 provides the experiment configurations. Section 4 presents the experiment results. Section 5 concludes the paper.

2. TIME-DOMAIN GENERALIZED WIENER FILTER

2.1. Conventional Filter-and-sum Beamformers

Given $M$ channels of $L$-sample noisy observations $\{y_m\}_{m=1}^M$, $y_m \in \mathbb{R}^{1 \times L}$ and a source-of-interest (SOI) $x \in \mathbb{R}^{1 \times L}$, a standard filter-and-sum beamformer estimates $M$ beamformer coefficients $\{h_m\}_{m=1}^M$, $h_m \in \mathbb{R}^{1 \times K}$ which are applied to $\{y_m\}_{m=1}^M$:

$$\hat{x} = \sum_{m=1}^M y_m \odot h_m$$

(1)

where $\odot$ denotes the convolution operation, $K$ denotes the length of the beamformer coefficients, and $\hat{x} \in \mathbb{R}^{1 \times L}$ is the estimated SOI.

Such beamforming process is typically done in the frequency domain:

$$\hat{x}(f) = \sum_{m=1}^M y_m(f)h_m(f) = h(f)^H Y(f)$$

(2)

where $\hat{x}(f), y_m(f) \in C^{1 \times T}$ denotes the $f$-th frequency component in the spectrogram of $\hat{x}, y_m$, respectively, $T$ denotes the number of frames in the spectrograms, $h_m(f) \in C$ denotes the beamformer.
coefficient for the \( m \)-th channel at the \( f \)-th frequency component, \( Y(f) \in \mathbb{C}^{M \times T} \) and \( h(f) \in \mathbb{C}^{M \times 1} \) represent the concatenation of the \( f \)-th frequency components and beamformer coefficients across all \( M \) channels, respectively, and \((\cdot)^H\) stands for the conjugate transpose.

The estimation of \( h(f) \) can be done by solving certain optimization problems designed for various purposes. For example, the frequency-domain MCWF (FD-MCWF) is defined for the MMSE estimation between the beamformed output and the estimated SOI, and its closed-form solution is:

\[
h_{\text{MCWF}}(f) = (Y(f)Y(f)^H)^{-1}Y(f)x(f)^H
\] (3)

### 2.2. Time-domain Generalized Wiener Filter

Figure 1 shows the procedure of the proposed TD-GWF. Note that the separation modules: a pre-separation module, a beamformer, and a post-enhancement module. The pre-separation module first performs separation on the noisy observations to obtain a coarse estimation of the SOIs, and then the beamformer uses those estimations to calculate the beamformer coefficients. The beamformed outputs, typically together with the coarse estimations from the pre-separation module, are then sent to a post-enhancement module for further refinements. Such beamforming-refinement procedure can be repeated for multiple iterations to form a sequential neural beamforming pipeline. Current pipelines have investigated the use of FD-MCWF and FD-MVDR beamformers in the pipeline and reported significant performance improvements compared to separator-only or single-stage neural beamforming baselines.

The application of TD-GWF in the existing sequential neural beamforming pipeline is straightforward. Figure 2 shows the pipeline of TD-GWF-based sequential neural beamformer. We follow the general design of [14] and [17] on the use of a single-channel separation network for both the pre-separation and the post-separation modules to save the computational cost, and we replace the FD-MCWF by the proposed TD-GWF. Moreover, we adopt the pipeline in [15] where each beamforming-refinement procedure is treated as one iteration, and the post-separation module receives the concatenation of the noisy observation at the reference channel, the separation outputs at previous iteration (the pre-separation outputs for the first iteration), and the TD-GWF outputs at the current iteration as inputs. The network parameters for the post-separation module is shared across all iterations. The training of the entire system is done by calculating the training objective on all outputs of the separation modules:

\[
\mathcal{L}_{\text{obj}} = \frac{1}{K} \sum_{k=1}^{K} D(\mathcal{T}(\mathbf{X}^{(k)}_{v}, C_{c=1}^{c}, \mathbf{X}_{c}^{(c=1)})
\] (8)

where \( C \) denotes the total number of SOIs, \( K \) denotes the number of beamforming-refinement iterations, \( D(\cdot) \) is a selected loss function, and \( D(\cdot) \) denotes the application of permutation invariant training (PIT) [18].
2.4. Discussions

2.4.1. Relationship with Conventional Frequency-domain Beamformers

TD-GWF can be related to the conventional frequency-domain beamformers in two ways. On the one hand, it follows the general problem formulation of conventional beamformers where an optimization problem is defined on an estimated SOI to solve the beamformer coefficients. This can be easily observed since equations 3 and 5 only have differences on the dimension of the features and whether the operations are done in time-domain or frequency-domain. On the other hand, when the number of groups $V$ equals to the feature dimension $N$, the TD-GWF coefficients are calculated on each feature dimension independently, and the shape of the coefficients becomes $M \times 1$. If we do not use the real-valued waveform encoder $B$ but use the Fourier transform to extract the sequential features, TD-GWF with $V = N$ falls back to the FD-MCWF in equation 3.

2.4.2. The Effect of Group Size

The group size $V$ not only connects to the conventional beamformers when $V = N$, but also controls the overall model complexity. The concatenation of $\{\hat{X}_v\}_{v=1}^V$ across groups can be rewritten as the multiplication of two block-diagonal matrices:

$$
\hat{X} = \begin{bmatrix}
W_1^T & \cdots & 0 \\
\vdots & \ddots & \vdots \\
0 & \cdots & W_V^T
\end{bmatrix}
\begin{bmatrix}
\hat{Y}_1 & \cdots & 0 \\
\vdots & \ddots & \vdots \\
0 & \cdots & \hat{Y}_V
\end{bmatrix}
$$

(9)

For $V = 1$, $W_v \in \mathbb{R}^{MN \times N}$ has no off-diagonal zero blocks and requires the most amount of float-point operations. A larger $V$ increases the number of off-diagonal zero blocks and saves the computational cost, while at the cost of a fewer degrees of freedom. For $V = N$, the coefficient matrix becomes a diagonal matrix and is equivalent to the Hadamard product between the features of the noisy observations and the coefficients, which again falls back to the standard formulation of frequency-domain filtering.

3. EXPERIMENT CONFIGURATIONS

3.1. Dataset

We evaluate the proposed TD-GWF on a simulated noisy reverberant two-speaker dataset. 20000, 5000 and 3000 4-second long utterances are simulated at 16k Hz for training, validation and test sets, respectively. For each utterance, two speech signals and one noise signal are randomly selected from the 100-hour Librispeech subset [19] and the 100 Non-speech Corpus [20], respectively. The overlap ratio between the two speakers is uniformly sampled between 0% and 100%, and the two speech signals are shifted accordingly and rescaled to a random relative signal-to-noise-ratio (SNR) between 0 and 5 dB. The relative SNR between the speech mixture and the noise is randomly sampled between 10 and 20 dB. The transformed signals are then convolved with the room impulse response filters simulated by the image method [21] using the gpuRIR toolbox [22]. We refer the interested readers to [23] for a more detailed description on the room configurations. In this paper we only use the fixed geometry array dataset, in which a circular array with 6 evenly-distributed microphones with 10 cm diameter is randomly placed. The average distance between the SOIs and the array center is 2.9±1.6 meters.

Table 1. Oracle performance of frequency-domain MCWF and the proposed TD-GWF. Oracle clean reverberant SOIs are used for the calculation of the beamformer coefficients.
### 3.2. Model configurations

We use the single-channel DPRNN-TasNet model [24] for the pre-separation and post-separation modules in the sequential neural beamforming pipeline where each module contains 3 DPRNN blocks. The window size and hop size in the TasNet’s waveform encoder and decoder are set to 2 ms (32 samples) and 1 ms (16 samples), respectively, and the number of filters in the encoder and decoder is set to 64. The input size and hidden size of the LSTM layers in the DPRNN blocks are set to 64 and 128, respectively. The separation is done by estimating a set of multiplicative masks applied to the TasNet’s encoder outputs, and we use a ReLU activation on the mask estimation layer to generate nonnegative masks.

For the TD-GWF module, we set the waveform encoder \( B \) to identity matrix \( I \), which means that we only window the waveforms without applying a waveform encoder (note that \( B \) is different from the TasNet’s encoder). The window size \( P \) for TD-GWF is set to 2 ms, 4 ms, 8 ms, and 16 ms for performance comparison, and the hop size is set to 25% of the window size \( P \) according to the common configurations in frequency-domain beamformers. The feature dimension \( N \) equals to the window size \( P \).

### 3.3. Training and Evaluation

All models are trained for 100 epochs with the Adam optimizer [25] with an initial learning rate of 0.001. Signal-to-noise ratio (SNR) is used as the training objective \( D(\cdot) \), and the clean reverberant SOIs are used as the training targets. The learning rate is decayed by 0.98 for every two epochs. Gradient clipping by a maximum gradient norm of 5 is applied, and the gradients are blocked between different beamforming-refinement iterations. We report the signal-to-distortion ratio (SDR) [26] and the scale-invariant signal-to-distortion ratio (SI-SDR) [27] for signal quality evaluation.

### 4. RESULTS AND DISCUSSIONS

#### 4.1. Oracle Performance Comparison

We first compare the oracle performance of FD-MCWF and the proposed TD-GWF. Table 2 presents the separation performance of various sequential neural beamforming pipelines. The first two rows provide the separation results of the single-channel-only baselines, where “-S” and “-L” denote “small” and “large” models with 3 and 6 DPRNN blocks, respectively. The rest of the table contains the results for the sequential neural beamforming pipelines with either FD-MCWF or TD-GWF for the beamforming stage. We can see that the TD-MCWF with 32 ms window is significantly worse than the TD-GWF with only 2 ms window in both 1 and 2 iteration configurations. While the FD-MCWF with 512 ms window can have better separation performance than the TD-GWF when speaker angle or the overlap ratio is small, the size of the spatial covariance matrix is too large \((\mathbb{C}^{4097 \times 4097})\) so that the computational cost is much higher than that of TD-GWF (with \( W_v \in \mathbb{R}^{512 \times 64} \) for 4 ms window). We also notice that the performance of TD-GWF with 8 ms window is slightly worse than that with 2 ms and 4 ms windows, and a possible reason for it is that the 8 ms window configuration leads to a large filter coefficient matrix \( W_v \in \mathbb{R}^{768 \times 128} \), which contains even more entries than the 4-second long utterances with 64000 samples. We suspect that large window sizes might be more useful and important for longer utterances, and we leave the validation of it as future work with a more diverse and realistic dataset.

#### 4.2. Sequential Neural Beamforming with Different Numbers of Iterations

Table 2 presents the separation performance of various sequential neural beamforming pipelines. The first two rows provide the separation results of the single-channel-only baselines, where “-S” and “-L” denote “small” and “large” models with 3 and 6 DPRNN blocks, respectively. The rest of the table contains the results for the sequential neural beamforming pipelines with either FD-MCWF or TD-GWF for the beamforming stage. We can see that the TD-MCWF with 32 ms window is significantly worse than the TD-GWF with only 2 ms window in both 1 and 2 iteration configurations. While the FD-MCWF with 512 ms window can have better separation performance than the TD-GWF when speaker angle or the overlap ratio is small, the size of the spatial covariance matrix is too large \((\mathbb{C}^{4097 \times 4097})\) so that the computational cost is much higher than that of TD-GWF (with \( W_v \in \mathbb{R}^{512 \times 64} \) for 4 ms window). We also notice that the performance of TD-GWF with 8 ms window is slightly worse than that with 2 ms and 4 ms windows, and a possible reason for it is that the 8 ms window configuration leads to a large filter coefficient matrix \( W_v \in \mathbb{R}^{768 \times 128} \), which contains even more entries than the 4-second long utterances with 64000 samples. We suspect that large window sizes might be more useful and important for longer utterances, and we leave the validation of it as future work with a more diverse and realistic dataset.

### 5. CONCLUSION

We proposed the time-domain generalized Wiener filter (TD-GWF) as an alternative to conventional frequency-domain beamformers for multi-channel speech separation. TD-GWF has the advantage of a higher oracle performance and only contains real-valued operations, which makes it possible to apply any existing neural networks to any part of the filtering process. Experiment results on the sequential neural beamforming pipeline showed its effectiveness. Future works include the investigation of different group sizes, the use of different separator modules in the sequential neural beamforming pipeline, and the extension of TD-GWF to other forms of beamformers.

| Model                  | # of param. | # of iter. | Average |
|------------------------|-------------|------------|---------|
| DPRNN-TasNet-S         | 1.3M        | 1.4        | 8.3     |
| DPRNN-TasNet-L         | 2.6M        | 1.4        | 8.6     |
| FD-MCWF-TasNet (32 ms) | 13.6        | 1.4        | 9.2     |
| FD-MCWF-TasNet (512 ms)| 2.6M        | 1.4        | 10.5    |
| TD-GWF-TasNet (2 ms)   | 1.4         | 1.4        | 11.5    |
| TD-GWF-TasNet (4 ms)   | 1.4         | 1.4        | 11.5    |
| TD-GWF-TasNet (8 ms)   | 1.4         | 1.4        | 11.1    |

Table 2. Comparison of different models on the simulated 6-mic circular array. SI-SDR is reported on decibel scale.
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