Low-latency Monaural Speech Enhancement with Deep Filter-bank Equalizer

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It is highly desirable that speech enhancement algorithms can achieve good performance while keeping low latency for many applications, such as digital hearing aids, acoustically transparent hearing devices, and public address systems. To improve the performance of traditional low-latency speech enhancement algorithms, a deep filter-bank equalizer (FBE) framework was proposed, which integrated a deep learning-based subband noise reduction network with a deep learning-based shortened digital filter mapping network. In the first network, a deep learning model was trained with a controllable small frame shift to satisfy the low-latency demand, i.e., \( \leq 4 \) ms, so as to obtain (complex) subband gains, which could be regarded as an adaptive digital filter in each frame. In the second network, to reduce the latency, this adaptive digital filter was implicitly shortened by a deep learning-based framework, and was then applied to noisy speech to reconstruct the enhanced speech without the overlap-add method. Experimental results on the WSJ0-SI84 corpus indicated that the proposed deep FBE with only 4-ms latency achieved much better performance than traditional low-latency speech enhancement algorithms in terms of the indices such as PESQ, STOI, and the amount of noise reduction.

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I. INTRODUCTION

In modern digital hearing aids (Popelka et al., 2016; Proakis and Manolakis, 1996), speech enhancement plays a potentially important role in noisy environments in improving speech intelligibility and perceptual quality. This is because the speech reception threshold (SRT) of hearing-impaired (HI) listeners is often much higher than that of normal-hearing (NH) listeners, owing to reduced temporal and spectral resolution. In the last half-century, many efforts have been made to reduce noise for both monaural and bilateral hearing aids, so as to improve speech intelligibility, listening comfort and speech quality. For NH individuals, speech enhancement usually has not been found to improve speech intelligibility, but it can improve the speech perceptual quality and listening comfort by removing noise components without degrading intelligibility (Alcántara et al., 2003; Holube et al., 1999). Speech enhancement has already become a preprocessing step for many systems, such as audio-visual conference systems, public address systems, speech recognition systems, and hearing assistive devices.

Deep learning-based methods have become the current state-of-the-art for many signal processing problems.
ments when noise reduction algorithms are implemented in the T-F domain, where the length of the analysis/synthesis window should be large enough, e.g., 20-40 ms. This causes a relatively high system latency, since the signal delay depends on the synthesis window used for the overlap-add (OLA) reconstruction of the output. For many practical systems, such as digital hearing aids, acoustically transparent hearing devices and public address systems, low latency is required (Stone et al., 1999, 2008). Taking digital hearing aids as an example, the propagation time differences via air conduction and the overlap of spectral details, which makes it harder for deep neural networks (DNN) to learn speech spectral patterns be negligible, since each subband has a limited bandwidth. The subband-domain response of the FBE was estimated by a Noise Reduction Network (NR-Net) using the subband signals. Compared with traditional spectral-domain speech enhancement approaches, the NR-Net demonstrated powerful noise reduction ability by exploiting global filterbank correlations. In the second stage, a neural filter namely Filter Approximation network (FA-Net) was utilized to generate low-order time-domain filter coefficients to approximate the FBE subband-domain response. Then the input signal was filtered by the estimated filter via the overlap-save (OLS) synthesis method to reconstruct the time-domain enhanced output.

The contributions of this paper are two-fold. First, a novel deep learning-based speech enhancement framework for low latency applications was presented. To the best of our knowledge, this is the first time that a deep learning-based FBE framework for single-channel speech enhancement has been proposed and evaluated. Second, two neural filter design methods that approximate the FBE subband-domain response. In the time-domain signal reconstruction, the OLS method was adopted instead of the OLA method to reduce the system delay.

II. SIGNAL MODEL AND PROBLEM FORMULATION

The single-channel noisy mixture in the time domain is modeled as:

\[ x(t) = s(t) + n(t), \]  

(1)
where $s(t)$ denotes the clean speech, and $n(t)$ denotes the noise with $t$ the time index.

This paper adopts the framework for the adaptive FBE described by Lollmann and Vary (2007), which can achieve aliasing-free signal reconstruction for adaptive subband filtering and has a lower delay than the corresponding DFT AS FB. As shown in Fig. 2, the $M$ subband signals $x_i(t)$ are generated by means of $M$ band-pass filters with impulse responses $h_i(l)$ of length $L + 1$, given by

$$
x_i(k) = \sum_{l=0}^{L} x(kr-l)h_i(l); \quad i = 0, 1, \cdots, M-1,
$$

(2)

where $k$ is the frame index and $r$ is the downsampling rate. The impulse response of the $i$-th band-pass filter, $h_i(l)$, is a modulation of a prototype low-pass filter of length $L + 1 \geq M$ with the impulse response $h(l)$, given by

$$
h_i(l) = \begin{cases} h(l)\phi_i(l), & l \in \{0, 1, \cdots, L\}; i \in \{0, 1, \cdots, M-1\} \\
0, & \end{cases}
$$

(3)

In this work, we consider the generalized DFT (GDFT) with evenly-stacked frequency channels. Therefore, the impulse response of the prototype filter $h(l)$ and the general modulation sequence $\phi_i(l)$ are, respectively, given by:

$$
h(l) = \frac{1}{M} \sin\left(\frac{2\pi}{M}(l-\tau)\right) \text{win}(l)
$$

(4)

and

$$
\phi_i(l) = \exp\left(-j\frac{2\pi}{M}(l-\tau)\right), \quad i = 0, 1, \cdots, M-1; l \in \mathbb{Z},
$$

(5)

where $\text{win}(l)$ is the Hanning window, and $\tau = L/2$ is utilized to guarantee that the coefficients of the FIR filter have non-zero phase. This is important because a zero-phase FIR filter makes this system noncausal.

The enhanced signal is synthesized with the filter-bank summation (FBS) method as:

$$
\hat{s}(t) = \sum_{i=0}^{M-1} \hat{W}_i(k)x_i(k),
$$

(6)

where $\hat{W}_i(k)$ is the $i$-th subband response of the $k$th frame.

From Eqs. (2) and (3), Eq. (6) can be expressed as:

$$
\hat{s}(t) = \sum_{l=0}^{L} x(t-l)\hat{w}_l(k),
$$

(7)

where $\hat{w}_l(k)$ is the corresponding time-domain response of the estimated subband-domain response $\hat{W}_i(k)$.

The FBE is used to produce time-domain filter coefficients that can be updated in the subband-domain. The desired subband-domain response can be estimated by some speech enhancement algorithms, such as spectral subtraction, i.e., $\hat{W}_i(k) = \mathcal{F}_1(x_i(k))$, and the mapping between the subband-domain response and the time-domain high-order (HO) response is defined as $\hat{w}_l^{HD}(k) = \mathcal{G}_1(\hat{W}_i(k))$:

$$
\hat{w}_l^{HD}(k) = \mathcal{G}_1(\hat{W}_i(k)) = h(l)\sum_{i=0}^{M-1} \hat{W}_i(k)\phi_i(l),
$$

(8)

In order to further reduce signal delay, the response else can be approximated by a lower-degree filter which is denoted $\mathcal{G}_2(\cdot)$. The final time-domain response $\hat{w}_l(k)$ can be obtained after domain transformation $\mathcal{G}_1(\cdot)$ and the low-order filter approximation operation $\mathcal{G}_2(\cdot)$. The function for changing from the subband-domain response to the low-order time-domain response can be defined as $\hat{w}_l(k) = \mathcal{F}_2(\hat{W}_i(k))$.

To summarize, the implementation of the FBE consists of two stages: (1) Subband response estimation for noise reduction: in this stage, the mixture was decomposed into subband signals by the analysis filterbank with downsampling. Then the subband signals were used to calculate the subband-domain response of the noise-reduction filter. (2) Filter length shortening for latency reduction: in this stage, time-domain filter coefficients were obtained by a domain transform function and a low-order filter approximation operation. After that, the enhanced speech was generated by filtering the input signal with the estimated time-domain filter coefficients.

### III. PROPOSED TWO-STAGE FRAMEWORK

This section proposed a low-latency monaural speech enhancement framework with filter-bank equalizer that performed time-domain filtering with coefficients updated in the subband-domain by a DNN. Compared with the conventional FBE described in Section II, there
are three differences: (1) A masking-based neural network was utilized to estimate a subband-domain response which achieved better performance than traditional methods especially for low SNRs and non-stationary noise scenarios. (2) The filter approximation stage was replaced by a DNN in order to use a data-dependent method to fit the high-order filter rather than a fixed filter design method such as the MA filter approximation. In addition, we explored the effect of replacing the domain transformation mapping function with a network for the filter approximation and demonstrated better performance. (3) We implemented the filtering operation in the frequency domain with the OLS method instead of the OLA method when reconstructing the time-domain signal.

Figure 3(a) is a diagram of the proposed system, which consists of two stages, namely the Noise Reduction Network (NR-Net) and the Filter Approximation Network (FA-Net). The pipeline goes as follows. In the first stage, the full-band input signal was decomposed into M subband signals \( x_i(k) \) with \( i \in \{0, 1, \ldots, M - 1\} \). To reduce complexity, similar to Vary (2006), this subband decomposition was achieved via a polyphase network (PPN) implementation and downsampling in the analysis filterbank. After that, the NR-Net was employed to estimate the subband filter \( \hat{W} \in \mathbb{C}^{K \times M} \) to suppress the noise, where \( K \) is the number of frames.

To obtain time-domain filter coefficients for the full-band signal, in the second stage, the noisy signal \( x(t) \) was split into frames of \( M \) samples with frame shift \( r \):

\[
x^{DT}(k) = x[kr - M + 1 : kr], k \in \mathbb{Z},
\]

where \( x[a : b] \) means that samples of \( x(t) \) from time index \( a \) to time index \( b \) are included.

For the \( k \)th frame, the FA-Net received both the original noisy signal \( x^{DT}(k) \in \mathbb{R}^{M \times 1} \) and the estimated response \( \hat{W}(k) \) as the input and aimed to predict the corresponding frequency-domain response \( \hat{W}_{DFT}(k) \in \mathbb{C}^{D \times 1} \), where \( D \) depends on the degree of the approximate time-domain filter. Then the mixture signal \( x_{\text{filter}}(k) = x[kr - 2P + 1 : kr] \) was filtered by the estimated \( k \)th frame frequency-domain response \( \hat{W}_{DFT}(k) \) and the last \( r \) samples of the output were preserved as the enhanced output of the \( k \)th frame \( \hat{s}(k) \in \mathbb{R}^{r \times 1} \). The final enhanced signal was constructed using the OLS method. The whole forward calculation process was formulated as:

\[
\hat{W} = \mathcal{F}_1(X; \Theta_1),
\]

\[
\hat{W}_{DFT}(k) = \mathcal{F}_2(x^{DT}(k), \hat{W}(k); \Theta_2),
\]

\[
\hat{s}(k) = \mathcal{F}_3(\hat{W}_{DFT}(k), x_{\text{filter}}(k)),
\]

where \( X \in \mathbb{C}^{K \times M} \) with \( X_{i,k} = x_i(k) \). \( \mathcal{F}_1, \mathcal{F}_2, \) and \( \mathcal{F}_3 \) denote the calculation operations of NR-Net, FA-Net, and signal reconstruction, respectively. \( \Theta_1 \) and \( \Theta_2 \) are the network parameters of NR-Net and FA-Net, respectively.

A. Noise Reduction Network

A diagram of the Noise Reduction Network (NR-Net) is shown in Fig. 3(b) and Fig. 3(c). It is a convolutional recurrent network (CRN), which has been successfully applied in the field of speech enhancement (Tan and Wang, 2020).

The NR-Net is essentially an encoder-decoder structure with long short-term memory (LSTM) layers between the encoder and the decoder (Tan and Wang, 2020). The input is the 257-dimensional subband complex spectrum of the input signal. The encoder includes six convolutional blocks to extract spectro-temporal features from the noisy spectra, and the decoder has six deconvolutional blocks to gradually interpolate and recover the original size of the input and estimate the complex mask. Each (de)convolutional block comprises a...
(De)Conv-GLU layer, batch normalization (BN) and an ELU activation layer. In order to obtain a causal system for real-time processing, we applied causal convolutions in the time dimension to the encoder and decoder layers, which were utilized to control the output at time $t$ based only on the input features from time $t$ and earlier in the previous layer, meanwhile maintain the temporal order of the input sequence. Note that causal convolutions can be easily applied to the decoder layers because the deconvolution is essentially a convolution operation. Within each layer, the kernel size was set to $1 \times 3$ except for the first layer, where it was $1 \times 5$ and the stride was $1 \times 2$ along the time and frequency directions to keep all layers the same time dimension to meet the real-time requirement and obtain a large-range receptive field along the frequency axis to learn the characteristics of inter-harmonic features. The number of channels of each convolutional block in the encoder was set to 16, 32, 64, 64, 128, 256 from the first to the last one. The decoder was designed as a mirror version of the encoder, and the number of channels of the final deconvolutional layer was set to 2 without normalization and activation function to estimate the complex subband-domain mask. In this way, low-resolution feature embedding was transformed by the encoder and the decoder restored high-level features to the spectra with the original input shape. To mitigate the gradient disappearance problem, the skip connection strategy was adopted, which concatenated the output of each encoder layer and that of the corresponding decoder layer. Between the encoder and the decoder, two LSTM layers were inserted to capture temporal sequence dependencies. To reduce the model complexity, a grouping strategy was adopted for each LSTM layer (dubbed GLSTM), where the group number was set to 4.

A more detailed description of NR-Net is presented in Table I. The input size and the output size are given in $(ChannelNum \times TimeSteps \times frequencySize)$ for both the encoder and the decoder, and $(TimeSteps \times frequencySize)$ for LSTMs. The hyper-parameters for CNNs are specified with $(KernelSize, Strides, ChannelNum)$ format.

### B. Filter Approximation Network

The Filter Approximation Network (FA-Net) is shown in Fig. 3 (d). It consists of stacked LSTM layers. The segmented noisy signal and the predicted complex subband-domain response were taken as the input, and passed through a batch normalization layer and an LSTM layer to generate the embedding $\mathbf{X}^e$ and $\mathbf{W}^e$, given by

$$\mathbf{X}^e = \mathcal{H}_x(BN(x^{DFT}(k))),$$

$$\mathbf{W}^e = \mathcal{H}_w(BN(\hat{W}(k))),$$

where $\mathcal{H}_x(\cdot)$ and $\mathcal{H}_w(\cdot)$ are the mapping functions defined by the LSTM, and $BN(\cdot)$ is the batch normalization. Then we concatenated $\mathbf{X}^e$ and $\mathbf{W}^e$ and sent to an LSTM layer to create an embedding function $\mathbf{E}^e$.

$$\mathbf{E}^e = \mathcal{H}([\mathbf{X}^e, \mathbf{W}^e]),$$

where $\mathcal{H}(\cdot)$ is the LSTM function, and $[\cdot, \cdot]$ represents the concatenate operation.

After that, two FC layers were utilized to estimate the real and imaginary parts of the corresponding frequency response of $\hat{W}(k)$, i.e.,

$$\hat{W}^r_{DFT}(k) = G^r_{DFT} \mathbf{E}^e + b^r_{DFT},$$

where $G^r_{DFT}$ and $b^r_{DFT}$ are the weight and bias of the FC layer, respectively. The superscripts $r$ and $i$ denote the real and imaginary parts, respectively. $\hat{w}(k)$ could be obtained by calculating the inverse DFT (iDFT) of $\hat{W}_{DFT}(k) = \hat{W}^r_{DFT}(k) + j\hat{W}^i_{DFT}(k)$.

### C. Signal Reconstruction

To train the system in an end-to-end manner in the second stage, we performed the filtering operation in the frequency domain according to the convolution theorem. Specifically, we first segmented the noisy waveform into chunks of length 2P and hop size $r$, $x^{filter} \in \mathbb{R}^{T \times 2P}$. For the $k$th frame, the filtering result $\hat{S}(k)$ could be obtained by multiplying the DFT of $x^{filter}(k)$ and $\hat{W}_{DFT}(k)$, given by

$$\hat{S}(k) = DFT\{x^{filter}(k)\} \hat{W}_{DFT}(k),$$

Finally, the last $r$ samples of the iDFT of $\hat{S}(k)$ were selected as the enhanced output of the $k$th frame, given as:

$$\tilde{s}(k) = iDFT\{\hat{S}(k)\}[2P - r + 1 : 2P].$$

### D. Loss Function

The mean squared error (MSE) $\mathcal{L}^{RI+Mag}$ was used as the loss function, which led to higher scores on speech quality and intelligibility metrics, that was

$$\mathcal{L}^{RI+Mag} = \mathcal{L}^{RI} + \mathcal{L}^{mag},$$

where

$$\mathcal{L}^{RI} = \|\hat{S}_r - S_r\|_F^2 + \|\hat{S}_i - S_i\|_F^2,$$

$$\mathcal{L}^{mag} = \|\hat{S}_r + j\hat{S}_i| - |S_i\|_F^2,$$

where $\hat{S}_r$ and $\hat{S}_i$ are the predicted real and imaginary parts of the clean speech, and $\cdot$ extracts magnitude. $S_r$ and $S_i$ are the real and imaginary components of the clean speech.

In this paper, a two-stage training strategy was applied to train the network. First, we trained the NR-Net with the CRM-based signal approximation loss. $\hat{S}_r$ and $\hat{S}_i$ were defined as $\hat{W}_rX_r$ and $\hat{W}_iX_i$, respectively.

Then the parameters of NR-Net were frozen and we only train FA-Net. The MSE loss calculated from the
TABLE I. Architecture of the NR-Net model used in this paper.

| layer name       | input size | hyper-parameters | output size |
|------------------|------------|------------------|-------------|
| Conv_1           | $3 	imes 1 	imes 257$ | $1 	imes 5, (1, 2), 16$ | $3 	imes 1 	imes 127$ |
| Conv_2           | $16 	imes 1 	imes 127$ | $1 	imes 3, (1, 2), 32$ | $32 	imes 1 	imes 63$ |
| Conv_3           | $32 	imes 1 	imes 63$ | $1 	imes 3, (1, 2), 64$ | $64 	imes 1 	imes 31$ |
| Conv_4           | $64 	imes 1 	imes 31$ | $1 	imes 3, (1, 2), 64$ | $64 	imes 1 	imes 15$ |
| Conv_5           | $64 	imes 1 	imes 15$ | $1 	imes 3, (1, 2), 128$ | $128 	imes 1 	imes 7$ |
| Conv_6           | $128 	imes 1 	imes 7$ | $1 	imes 3, (1, 2), 256$ | $256 	imes 1 	imes 3$ |
| reshape_size_1   | $64 	imes 1 	imes 4$ | - | $1 	imes 768$ |
| reshape_size_2   | $T 	imes 768$ | $T 	imes 768$ | $T 	imes 768$ |
| GLSTM_1          | $T 	imes 768$ | $T 	imes 768$ | $T 	imes 768$ |
| DeConvGLU_1      | $512 	imes 1 	imes 3$ | $1 	imes 3, (1, 2), 128$ | $128 	imes T 	imes 7$ |
| DeConvGLU_2      | $256 	imes 1 	imes 7$ | - | $256 	imes T 	imes 7$ |
| DeConvGLU_3      | $64 	imes 1 	imes 15$ | - | $128 	imes T 	imes 15$ |
| DeConvGLU_4      | $128 	imes 1 	imes 15$ | $1 	imes 3, (1, 2), 64$ | $64 	imes T 	imes 31$ |
| DeConvGLU_5      | $64 	imes 1 	imes 31$ | - | $128 	imes T 	imes 31$ |
| DeConvGLU_6      | $32 	imes 1 	imes 31$ | $1 	imes 3, (1, 2), 32$ | $32 	imes T 	imes 63$ |

IV. EXPERIMENTAL SETUP

A. Dataset

We conducted the experiments on the WSJ0-SI84 corpus (Paul and Baker, 1992), which includes 7138 utterances by 83 speakers (42 males and 41 females). Of these speakers, we set aside 6 speakers as untrained speakers, and 5428 and 957 utterances by 77 remaining speakers were chosen for training and validation, respectively. The noise clips were provided by the DNS-Challenge (Reddy et al., 2020) and we randomly selected 20,000 recordings as the noise set, with a total duration of about 55 hours. The noisy signal was generated as follows: a noise vector was generated by randomly cutting from the noise dataset, and then mixed with a randomly selected clean utterance at a randomly selected SNR. The SNR was set to range from -5 dB to 0 dB in 1-dB steps.

During the model evaluation, two test sets were created for each noise. One was based on noise mixed with clean speech utterances from 6 trained speakers, and the other was based on noise mixed with utterances from 6 untrained speakers to investigate speaker generalization capability of the method. Both test sets consisted of 3 males and 3 females. Three noise types were chosen for model evaluation, namely white Gaussian noise, babble noise, and factory1 noise from the NOISEX-92 dataset (Varga and Steeneken, 1993). This selection included stationary noise, impulsive, as well as speech-like noise types. Note that all these three types of noise were untrained in the training stage. Four SNRs were set, namely -5 dB, 0 dB, 5 dB, and 10 dB. In total, 150 mixtures were generated with $25 	imes 6$ utterances of 6 speakers for each case.

B. Parameter Setup

All the utterances were sampled at 16 kHz. The analysis filterbank had $M = 512$ band-pass filters with the length of a prototype filter $L = 512$, and a downsampling rate $r = 64$. The model was trained for 50 epochs using the Adam (Kingma et al., 2015) optimizer. The initialized learning rate (LR) was set to 0.001, and we halved the LR when the validation loss did not increase for two consecutive epochs. The batch size was set to 16 at the utterance level, and the maximum utterance length was set to 8 seconds.

C. Comparison Systems

We compared the performance of the proposed system with the following speech enhancement algorithms.

1) MMSE-MA-FBE: the FBE presented in Sec.II. The subband-domain response was computed by the minimum mean-square error log-spectral amplitude (MMSE-LSA) estimator (Ephraim and Malah, 1985), and the GDFT was applied to transform the response to the time-domain filter coefficients. Then the moving-average filter was utilized to approximate the time-domain filter of the FBE. To ensure the sig-
nal delay to 4 ms, the length of the MA filter $P$ was set to 128.

2) CRN-MA-FBE: the FBE was constructed using the subband-domain response of the FBE estimated by the NR-Net, followed by filter approximation using the MA filter with its length $P = 128$.

3) DeepFBE-T: the deep learning-based FBE implemented the domain transform by GDFT and used the DNN to learn the filter approximation mapping from time-domain filter coefficients of the FBE to the corresponding low-order filter. The NR-Net was first applied to estimate the subband-domain response of the FBE and then the GDFT of the response yields the time-domain filter coefficients of the FBE. The FA-Net was used to predict the corresponding low-order time-domain weighting factors, which were utilized to filter the mixture. A 256-point DFT was implemented since filter coefficients were padded with zeros to keep the same length as the input signal $x_{filter}(k) \in \mathbb{R}^{2P \times 1}$, with $P = 128$, in the frequency-domain signal reconstruction stage. Considering the symmetry of real-value filter coefficients in frequency, $D$ was set to 129 points.

4) DeepFBE: the deep learning-based FBE described in Sec.III. In contrast to the DeepFBE-T, the FA-Net directly built the mapping from the subband-domain response of the FBE to the frequency-domain response of the corresponding low-order approximate filter.

V. RESULTS

A. Objective measurements

Three commonly used objective measurements were chosen to evaluate the performance of the proposed deep FBE, including segmental noise attenuation (segNA) (Fingscheidt et al., 2008), perceptual evaluation of speech quality (PESQ) (Rix et al., 2001), and segmental SNR (segSNR) (Loizou, 2007). For completeness, three composite measures proposed in (Loizou, 2007) with reference to ITU-T P.835 standard including CSIG, CBAK and COVL were also selected as objective metrics to evaluate these models.

When computing the segNA, the residual noise $\hat{n}(t)$ needed to be separated from $\hat{s}(t)$. This was not a trivial task, and thus only noise-only frames were chosen to compute the segNA, because $\hat{n}(t) = \hat{s}(t)$ in this case, the segNA could be obtained as

$$\text{segNA} = 10 \log_{10} \left( \frac{1}{N_F} \sum_{m \in F} \sum_{\mu=0}^{M-1} n^2(mr + \mu) \right), \quad (22)$$

where $N_F$ denotes the total number of noise-only frames and $F$ indicates the indices of noise-only frames, i.e., $m \in F$. The higher segNA, the less residual noise remains, and the better is the noise reduction performance of the method.

The PESQ score, ranging from -0.5 to 4.5, was obtained from the clean speech $s(t)$ and the enhanced speech $\hat{s}(t)$. The higher the PESQ score, the better speech perceptual quality is.

The output segmental SNR is defined as:

$$\text{segSNR} = \frac{10}{A_F} \sum_{m \in A} \log_{10} \left( \frac{\sum_{\mu=0}^{M-1} s^2(mr + \mu)}{\sum_{\mu=0}^{M-1} (s(mr + \mu) - s(mr + \mu))^2} \right), \quad (23)$$

where $A$ means all frames.

For composite measures that aim to computationally approximate the Mean Opinion Score (MOS), the CSIG score is the MOS prediction of perceived signal distortion based only on the speech signal, the CBAK score measures the intrusiveness of background noise, and the COVL score represents the overall effect of the algorithm. All of them range from 1 to 5, where higher scores indicate better performance.

B. Objective Metrics for Trained Speakers

We evaluated and compared the systems using the WSJ0-SI84 trained speakers. Tables II, III, and IV report the results in terms of PESQ, segNA, segSNR, CSIG, CBAK, and COVL for each case. The average results across the three noises are shown in Fig. 4.

Several observations can be made. First, compared with MMSE-MA-FBE, the CRN-MA-FBE achieved better performance, especially for low SNRs and non-stationary noise scenarios. This is because it is difficult for the conventional noise estimation method to track rapid changes of noise power, resulting in speech distortion and remaining residual noise. For example, for babble noise, the CSIG scores of the MMSE-MA-FBE were lower than for the noisy mixture at SNR=-5dB, for which the MMSE-MA-FBE approach did not work at all, getting PESQ=1.78 and COVL=1.63, which was almost the same as the PESQ value of 1.77 and the COVL value of 1.63 for noisy speech. The CRN could suppress non-stationary noise better, and also achieved lower speech distortion. Besides, when a DNN replaced the MA filter approximation, it showed consistent improvements for all metrics over the competing methods for babble noise and factory1 noise, indicating that the filter approximated by the data-adaptive mapping was more beneficial for the speech enhancement task than a fixed filter design method. Finally, compared with DeepFBE-T, DeepFBE consistently outperformed DeepFBE-T in terms of PESQ, segSNR, CSIG, CBAK, and COVL. For speech distortion, compared with DeepFBE-T, DeepFBE achieved a 0.25 CSIG score improvement on average. For noise reduction, around 0.21 average improvement in CBAK is obtained, although the segNA decreased 2.51 dB on average. The reason is that segNA was computed with noise-only segments and DeepFBE-T had a powerful noise suppression capability for non-speech frames. Average 0.15, 1.60 dB and 0.23 increase in PESQ, segSNR and COVL scores were achieved, which showed that the quality of enhanced speech with DeepFBE could be im-
proven. This indicated that a non-constrained adaptive filter design was able to approximate the desired filter response better than a constrained method.

### C. Objective Metrics for Untrained Speakers

The evaluation results for untrained speakers are illustrated in Fig. 5, based on values averaged across the three types of noise. The results were consistent with those for the trained condition, showing that the proposed DeepFBE algorithm generalized very well to unseen speakers. Because less speech distortion and more noise reduction could be obtained by applying DNN to the FBE system, our system performed better than the competing methods, as expected. For example, the average difference in performance between DeepFBE and CRN-MA-FBE was 6.49 dB segNA, 2.36 dB segSNR, 0.31 PESQ, 0.33 CSIG, 0.39 CBAK and 0.36 COVL. These results indicated that utilizing the deep learning-based method to replace the traditional FBE results in better speech denoising performance with the same signal latency, which confirmed the effectiveness and generalization of the proposed deep-learning-based low-latency speech enhancement framework.

### D. Spectrogram Analysis

Finally, we analyzed the enhanced speech spectrograms processed by different methods. Fig. 6 (a) shows the spectrogram of the speech corrupted by white Gaussian noise at 0-dB SNR. Performance was improved when we replaced the MMSE-LSA with the CRN, which showed that the DNN could model the complex nonlinear relationship from the subband-domain features of

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**TABLE II. Objective result comparisons among different models in terms of PESQ, segNA, segSNR, CSIG, CBAK and COVL for white Gaussian noise in the trained speaker test set. ** **BOLD font indicates the best score in each case.**

| Metrics | Methods       | SNR (in dB) |
|---------|---------------|-------------|
|         |               | -5  | 0  | 5  | 10 | Avg. |
| PESQ    | Noisy         | 1.59| 1.80| 2.28| 2.08| 2.11 |
|         | MMSE-MA-FBE   | 1.84| 2.36| 2.78| 3.00| 2.52 |
|         | CRN-MA-FBE    | 2.21| 2.55| 2.86| 3.15| 2.69 |
|         | DeepFBE-T     | 2.36| 2.68| 2.98| 3.26| 2.82 |
|         | DeepFBE       | **2.52| **2.86| **3.16| **3.43| **2.99| |
| segNA   | Noisy         | -5.45| -2.49| 0.86| 4.48| -0.65 |
|         | MMSE-MA-FBE   | -1.43| 0.44| 2.99| 5.87| 1.97 |
|         | CRN-MA-FBE    | 0.23| 2.78| 5.64| 8.67| 4.33 |
|         | DeepFBE-T     | 2.18| 4.24| 6.03| 7.47| 4.98 |
|         | DeepFBE       | **2.74| **5.20| **7.47| **9.65| **6.27| |
| segSNR  | Noisy         | -5  | 0  | 5  | 10 | Avg. |
|         | MMSE-MA-FBE   | 1.85| 2.47| 3.10| 3.65| 2.77 |
|         | CRN-MA-FBE    | 2.84| 3.25| 3.65| 4.07| 3.45 |
|         | DeepFBE-T     | 2.18| 4.24| 6.03| 7.47| 4.98 |
|         | DeepFBE       | **3.09| **3.52| **3.89| **4.23| **3.68| |
| CSIG    | Noisy         | 1.50| 1.75| 2.05| 2.44| 1.93 |
|         | MMSE-MA-FBE   | 1.77| 2.03| 2.44| 2.89| 2.28 |
|         | CRN-MA-FBE    | 2.00| 2.36| 2.77| 3.22| 2.59 |
|         | DeepFBE-T     | 2.18| 2.49| 2.81| 3.11| 2.65 |
|         | DeepFBE       | **2.31| **2.70| **3.07| **3.42| **2.87| |
| CBAK    | Noisy         | 1.24| 1.47| 1.76| 2.15| 1.56 |
|         | MMSE-MA-FBE   | 1.42| 1.84| 2.39| 2.92| 2.14 |
|         | CRN-MA-FBE    | 2.04| 2.41| 2.83| 3.28| 2.64 |
|         | DeepFBE-T     | 2.07| 2.43| 2.82| 3.20| 2.63 |
|         | DeepFBE       | **2.29| **2.72| **3.13| **3.51| **2.91| |

**FIG. 4.** PESQ, segNA, segSNR, CSIG, CBAK and COVL scores under different SNRs for different methods in the trained speaker test set. Each value is averaged with three noise types.
TABLE III. Objective result comparisons among different models in terms of PESQ, segNA, segSNR, CSIG, CBAK and COVL for babble noise in the trained speaker test set. **BOLD** font indicates the best score in each case.

| Metrics | Methods       | SNR (in dB) | -5  | 0   | 5  | 10 | Avg. |
|---------|---------------|-------------|-----|-----|----|----|-----|
|         |               |             |     |     |    |    |     |
| PESQ    | Noisy         |             | 1.77| 2.04| 2.36| 2.69| 2.22 |
|         | MMSE-MA-FBE   |             | 1.78| 2.14| 2.51| 2.87| 2.52 |
|         | CRN-MA-FBE    |             | 1.96| 2.30| 2.66| 2.97| 2.47 |
|         | DeepFBE-T     |             | 2.08| 2.47| 2.85| 3.13| 2.63 |
|         | DeepFBE       |             | **2.19** | **2.58** | **3.00** | **3.30** | **2.77** |
| segNA   | Noisy         |             | -1.99| -2.02| 1.21| 4.86| -0.23 |
|         | MMSE-MA-FBE   |             | -1.42| 0.42 | 2.77| 5.53| 1.83 |
|         | CRN-MA-FBE    |             | -0.90| 1.42 | 4.31| 7.34| 3.04 |
|         | DeepFBE-T     |             | 0.54 | 2.67 | 4.71| 6.25| 2.54 |
|         | DeepFBE       |             | **3.05** | **2.52** | **2.86** | **3.13** | **2.71** |
| segSNR  | Noisy         |             | -4.99| -2.02| 1.24| 4.86| -0.23 |
|         | MMSE-MA-FBE   |             | -1.42| 0.42 | 2.77| 5.53| 1.83 |
|         | CRN-MA-FBE    |             | -0.90| 1.42 | 4.31| 7.34| 3.04 |
|         | DeepFBE-T     |             | 0.54 | 2.67 | 4.71| 6.25| 2.54 |
|         | DeepFBE       |             | **1.60** | **2.14** | **2.55** | **2.92** | **2.47** |
| CSIG    | Noisy         |             | 2.40 | 2.71 | 3.09| 3.53| 2.93 |
|         | MMSE-MA-FBE   |             | 2.35 | 2.73 | 3.20| 3.72| 3.00 |
|         | CRN-MA-FBE    |             | 2.75 | 3.12 | 3.53| 3.90| 3.33 |
|         | DeepFBE-T     |             | 0.54 | 2.67 | 4.71| 6.25| 2.54 |
|         | DeepFBE       |             | **3.04** | **2.52** | **2.86** | **3.13** | **2.71** |
| CBAK    | Noisy         |             | 1.42 | 1.71 | 2.07| 2.52| 1.93 |
|         | MMSE-MA-FBE   |             | 1.63 | 1.90 | 2.26| 2.72| 2.13 |
|         | CRN-MA-FBE    |             | 1.75 | 2.05 | 2.46| 2.88| 2.29 |
|         | DeepFBE-T     |             | 1.98 | 2.30 | 2.66| 2.96| 2.48 |
|         | DeepFBE       |             | **2.09** | **2.47** | **2.92** | **3.34** | **2.70** |
| COVL    | Noisy         |             | 1.65 | 1.86 | 2.16| 2.58| 2.06 |
|         | MMSE-MA-FBE   |             | 1.63 | 1.92 | 2.34| 2.85| 2.19 |
|         | CRN-MA-FBE    |             | 1.89 | 2.18 | 2.58| 2.97| 2.41 |
|         | DeepFBE-T     |             | 2.04 | 2.39 | 2.80| 3.16| 2.60 |
|         | DeepFBE       |             | **2.15** | **2.55** | **3.06** | **3.52** | **2.82** |

FIG. 5. PESQ, segNA, segSNR, CSIG, CBAK and COVL scores under different SNRs for different methods in the un-trained speaker test set. Each value is averaged with three noise types.

FIG. 6. Spectrograms of (a) noisy speech corrupted with white Gaussian noise at 0-dB SNR, and enhanced speech processed by (b) MMSE-MA-FBE, (c) CRN-MA-FBE, (d) DeepFBE-T and (e) DeepFBE, (f) clean speech.

which was consistent with the test results of the segNA metric, and DeepFBE showed the best performance overall. In non-stationary noise cases (see Figure 7 (b) and 8 (b) for details), MMSE-MA-FBE preserved a lot of residual background noise components and had significant speech distortion, which happened because the noise estimation of the MMSE-LSA method could not track large changes of non-stationary noise power spectral den-
| Metrics | Methods          | SNR (in dB) | -5 | 0  | 5  | 10  | Avg. |
|---------|------------------|-------------|----|----|----|-----|------|
|         |                  |             |    |    |    |     |      |
| PESQ    | Noisy            | 1.64        | 2.19 | 2.59 | 3.08 | 2.34 |
|         | MMSE-MA-FBE      | 1.84        | 2.21 | 2.59 | 3.02 | 2.39 |
|         | CRN-MA-FBE       | 2.03        | 2.39 | 2.74 | 3.04 | 2.55 |
|         | DeepFBE-T        | 2.18        | 2.55 | 2.89 | 3.15 | 2.69 |
|         | DeepFBE          | **2.26**    | **2.67** | **3.03** | **3.31** | **2.82** |
| segNA   | Noisy            | -1.71       | 0.35  | 2.72  | 5.43  | 1.70 |
|         | MMSE-MA-FBE      | -0.67       | 1.82  | 4.68  | 7.59  | 3.35 |
|         | CRN-MA-FBE       | 1.19        | 3.30  | 5.15  | 6.62  | 4.06 |
|         | DeepFBE-T        | **1.97**    | **4.53** | **7.00** | **9.28** | **5.69** |
|         | DeepFBE          | **1.97**    | **4.53** | **7.00** | **9.28** | **5.69** |
| segSNR  | Noisy            | 2.31        | 2.64  | 3.04  | 3.52  | 2.88 |
|         | MMSE-MA-FBE      | 2.29        | 2.68  | 3.12  | 3.59  | 2.92 |
|         | CRN-MA-FBE       | 2.79        | 3.16  | 3.57  | 4.00  | 3.38 |
|         | DeepFBE-T        | 2.89        | 3.25  | 3.63  | 3.99  | 3.44 |
|         | DeepFBE          | **3.04**    | **3.43** | **3.87** | **4.29** | **3.66** |
| CSIG    | Noisy            | 1.42        | 1.71  | 2.09  | 2.56  | 1.94 |
|         | MMSE-MA-FBE      | 1.65        | 1.92  | 2.27  | 2.71  | 2.14 |
|         | CRN-MA-FBE       | 1.79        | 2.13  | 2.55  | 3.01  | 2.37 |
|         | DeepFBE-T        | 2.05        | 2.36  | 2.69  | 3.01  | 2.53 |
|         | DeepFBE          | **2.15**    | **2.51** | **2.93** | **3.33** | **2.73** |
| CBAK    | Noisy            | 1.29        | 1.81  | 2.14  | 2.58  | 2.00 |
|         | MMSE-MA-FBE      | 1.61        | 1.90  | 2.28  | 2.76  | 2.14 |
|         | CRN-MA-FBE       | 1.92        | 2.24  | 2.66  | 3.12  | 2.49 |
|         | DeepFBE-T        | 2.06        | 2.39  | 2.78  | 3.18  | 2.60 |
|         | DeepFBE          | **2.17**    | **2.54** | **3.01** | **3.47** | **2.80** |

FIG. 7. Spectrograms of (a) noisy speech corrupted with babble noise at 0-dB SNR, and enhanced speech processed by (b) MMSE-MA-FBE, (c) CRN-MA-FBE, (d) DeepFBE-T and (e) DeepFBE, (f) clean speech.

FIG. 8. Spectrograms of (a) noisy speech corrupted with factory1 noise at 0-dB SNR, and enhanced speech processed by (b) MMSE-MA-FBE, (c) CRN-MA-FBE, (d) DeepFBE-T and (e) DeepFBE, (f) clean speech.

VI. CONCLUSION

In this paper, we proposed a deep learning-based filter-bank equalizer namely DeepFBE for low-latency speech enhancement. A subband adaptive filtering technique was applied to reduce the signal latency while maintaining the high frequency resolution. First, the subband-domain response was estimated by the NR-Net to suppress background noise. Then the FA-Net was utilized to build the mapping between the response in the subband-domain and the frequency-domain response of a low-order filter. We conducted experiments using the WSJ0-SI84 dataset. The results demonstrated that the proposed framework significantly outperformed the benchmarks in both stationary and non-stationary noise scenarios.
situations, and had good generalization toward untrained speakers. In the future, we aim to explore the work on model compression for DeepFBE to satisfy the low power consumption requirement of hearing aids, and investigate the effectiveness of our system in noisy and reverberant scenarios.

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