Single-Channel Speech Dereverberation using Subband Network with A Reverberation Time Shortening Target

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Abstract

This work proposes a subband network for single-channel speech dereverberation, and also a new learning target based on reverberation time shortening (RTS). In the time-frequency domain, we propose to use a subband network to perform dereverberation for different frequency bands independently. The time-domain convolution can be well decomposed to subband convolutions, and the inverse filter of RIR is a direct-path speech with a stationary property. The learning target for dereverberation is usually set as the direct-path speech or occasionally with some early reflections. This type of target suddenly truncates the reverberation, and thus it may not be suitable for network training, and leads to a large prediction error. In this work, we propose a RTS learning target to suppress reverberation and meanwhile maintain the exponential decaying property of reverberation, which will ease the network training, and thus reduce the prediction error and signal distortions. Experiments show that the subband network can achieve outstanding dereverberation performance, and the proposed target has a smaller prediction error than the target of direct-path speech and early reflections.

Index Terms: Speech dereverberation, Subband network, Reverberation time shortening

1. Introduction

Severe late reverberation brings significant damage to the quality and intelligibility of speech \(^1\) and will also cause performance degradation for back-end tasks such as automatic speech recognition (ASR) \(^2\). Normally, early reflections does not cause so much negative effect \(^3\). Speech dereverberation, especially the single-channel case, is still a challenging task.

Before deep neural network (DNN) has been widely used, the traditional dereverberation methods were based on statistical models and signal processing algorithms. The essential problem of dereverberation is the deconvolution between speech signal and room impulse response (RIR). Deconvolution can be accomplished by applying an inverse filter of RIR to the reverberant speech, which is referred to as inverse filtering methods, \(^4\), \(^5\), \(^6\). As for the inverse filtering methods, accurate RIR must be first blindly identified, which is very challenging especially for the single-channel case \(^7\). Even if the RIR is known, due to its non-minimum phase characteristics in typical cases, directly computing its inverse filter will cause system instability or non-causality \(^8\), \(^9\). Moreover, inverse filtering is very sensitive to noise. Alternatively, instead of resolving the inverse filter of RIR, weighted prediction error (WPE) \(^10\), \(^11\) uses linear prediction to directly estimate the inverse filter from reverberant signal, and applies the inverse filter to remove late reverberation. WPE has achieved remarkable performance, and is one of the most popular dereverberation methods. Another technical line of dereverberation is spectral subtraction, following the perspective of speech enhancement. Late reverberation can be considered as additive noise, which is assumed to be independent of direct path signal and early reflections \(^12\), \(^13\). In \(^14\), methods for estimating the power spectrum density (PSD) of late reverberation have been summarized, such as convolutive transfer function (CTF)-based statistical model, maximum likelihood, coherent-to-diffuse power ratio (CDR), etc.

The application of DNN has made a great progress in solving single-channel speech dereverberation. The basic idea is to construct a nonlinear mapping function, based on supervised learning of DNN, from the features of reverberant speech to the features of target speech. The input features could be directly the time-domain signal, or the STFT (short-time Fourier transform) coefficients or magnitude spectrum of reverberant speech. Correspondingly, the output features could be the time-domain signal, STFT coefficients, magnitude spectrum or magnitude mask of target speech. The network architecture used for single-channel speech dereverberation has been evolved a lot, and made a great progress, from the initial fully connected networks \(^15\), \(^16\) to recurrent neural networks (RNN) with long short-term memory (LSTM) for time series modeling \(^17\), \(^18\), and to convolutional neural networks (CNN), such as U-NET \(^19\), \(^20\) and temporal convolutional networks (TCN) \(^21\), then to (self-)attention-based methods \(^22\), \(^23\).

Above mentioned DNN methods all take fullband input and output, aiming at learning the fullband spectral pattern of speech. This work proposes to use a subband network for single-channel speech dereverberation. In the STFT domain, different frequencies are processed independently by the same subband network. For one frequency, the network takes as input the STFT coefficients of this frequency and some neighbour frequencies of the reverberant speech, and outputs the STFT magnitude of this frequency of the target speech. A similar network was first proposed in our previous work \(^24\), \(^25\) for speech denoising, in which the network was designed to learn the local (subband) spectral pattern and different signal properties of speech and noise, such as the stationarity and spatial correlation of speech and noise. In this work, we revise this subband network to perform speech dereverberation. The rationality is that: the time-domain (fullband) convolution between speech and RIR can be decomposed into subband convolutions \(^4\), and the decomposition is almost lossless, then deconvolution can be performed in the subband to fully recover source speech. The subband network can be seen as a subband inverse filtering network. Experiments show that it is indeed able to achieve outstanding dereverberation performance.

Moreover, this work proposes a new learning target based

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on reverberation time shortening (RTS). DNN-based methods in the literature normally takes the direct-path speech as learning target, which actually is a very strict target as removing all reverberation. As a result, they normally have a large prediction error, which may cause speech distortion. Since early reflections do not cause speech quality degradation, they are often preserved and only late reverberation are removed, such as in WPE [10, 11] and the spectral subtraction methods [14]. Preserving early reflections in the learning target would reduce the prediction error of the network. However, preserving only early reflections will reduce the sound naturalness, as a real sound appears in natural environments would never have a such reverberation form. In addition, no matter which training target is used, the direct path or early reflections, the network need to learn a sudden removal (truncation) of reverberation, which is not fully suitable for network training and will cause a large prediction error. The proposed learning target is a shortened version of the original RIR, which has a small target $T_{60}$, e.g. 0.15 s. Instead of suddenly truncating RIR, the proposed learning target still maintains the property of exponential decay, which will maintain the sound naturalness and also ease the network training. Experiments show that the proposed learning target indeed has a lower prediction error, and thus less signal distortion.

2. The Proposed Method

Consider single-channel signals in the time domain:

$$y(n) = s(n) * a(n),$$

where * stands for convolution, $n$ denotes the discrete time index. $y(n), s(n)$, and $a(n)$ are reverberant speech, clean speech and room impulse response, respectively. This work focuses on dereverberation, and does not consider noise.

We can divide RIR $a(n)$ into two parts, where $a_d(n)$ and $a_u(n) = a(n) - a_d(n)$ are the desired and undesired parts, respectively. The reverberant speech can be rewritten as:

$$y(n) = s(n) * a_d(n) + s(n) * a_u(n) = x(n) + u(n)$$

This work aims to recover the desired signal $x(n)$ from the reverberant speech $y(n)$ and remove the undesired signal $u(n)$.

Setting the learning target as the direct path speech or with some early reflections amounts to applying a rectangular window $w(n)$ to RIR to obtain the desired part of RIR, i.e. $a_d = w_{rect}(n)a(n)$. The rectangular window for direct path and 50 ms of early reflections are shown in Fig. 1(a). The rectangular window suddenly truncates the RIR, as shown in Fig. 1(b) and (c) for the target of direct path and early reflections, respectively. This may make the neural network hard to learn the mapping function between the input and the output, and leads to a large prediction error and signal distortion.

2.1. Learning Target: Reverberation Time Shortening

In this work, we propose a new learning target based on RTS, which is a shortened version of the original RIR, and has a small target $T_{60}$, e.g. 0.15 s. Instead of suddenly truncating the RIR, the RTS target still maintains the property of exponential decay, which will maintain the sound naturalness and also ease the network training.

Formally, we define the new window function as:

$$w(n) = \begin{cases} 
1 & \text{for } n \leq N_1 \\
10^{-q(n-N_1)} & \text{for } n > N_1 
\end{cases}$$

$$a(n) \approx b(n)10^{-p(n-N_1)} \quad \text{for } n > N_1$$

where $N_1$ denotes the discrete time index when the direct path ends. The parameter $q$ controls the decaying rate of the window. The original RIR would be shortened by applying this window.

In Polack’s Statistical Model [26], the reverberation component of RIR can be realized by a Gaussian process with an exponentially decaying envelope. Based on this model, RIR can be written in the form of:

$$a(n) \approx b(n)10^{-p(n-N_1)} \quad \text{for } n > N_1$$

which is still exponentially decaying, with a new decaying rate of $p + q$.

Based on the definition of $T_{60}$, namely power decaying by 60 dB, the original $T_{60}$ of $a(n)$ and the new $T_{60}$ of $a_d(n)$ (denoted as $T_{60}'$) are respectively

$$T_{60} = \frac{3}{p f_s}, \quad T_{60}' = \frac{3}{(p + q) f_s},$$

where $f_s$ denotes the sampling frequency. It is obvious that $T_{60}'$ is smaller than $T_{60}$ as long as $q$ is positive.

In practice, we set the learning target with a desired $T_{60}'$. Given the original and target $T_{60}$, the window parameter $q$ is set to:

$$q = \frac{3}{T_{60} f_s} - \frac{3}{T_{60}' f_s},$$

Fig. 1(a) shows the window function for the case where $T_{60} = 0.7 s$ and $T_{60}' = 0.15 s$, and Fig. 1(d) shows the corresponding desired part of RIR.

2.2. Subband Deep Inverse Filtering

 Applying STFT to Eq. (1), and using the narrow-band assumption, we have

$$Y(k, p) \approx S(k, p)A(k),$$

where $N_1$ denotes the discrete time index when the direct path ends. The parameter $q$ controls the decaying rate of the window. The original RIR would be shortened by applying this window.

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where \( p \in [1, P] \) and \( k \in [0, K - 1] \) denote the frame and frequency indices, \( Y(k, p) \) and \( S(k, p) \) are the STFT coefficients of \( y(n) \) and \( x(n) \), \( A(k) \) is the Fourier transform of \( a(n) \). This assumption is only valid when RIR is very short.

The accurate relation between \( Y(k, p) \) and \( S(k, p) \) can be represented by the cross-band filters model [4]:

\[
Y(k, p) = \sum_{k'} S(k', p) \ast A(k, k')
\]

where convolution is applied along \( p \). \( Y(k, p) \) is a summation over multiple convolutions (between \( S(k, p) \) and filter \( A(k, k') \)) across frequencies \( k' \). In theory, to make the equation fully valid, \( k' \) should take all the frequencies. However, taking the range of \([k - l, k + l]\) (normally \( l = 4 \), determined by the bandwidth of the mainlobe of STFT window) for \( k' \) is enough to make the equation sufficiently valid. This means only a few frequency neighbors of \( S(k, p) \) make the main contribution to \( Y(k, p) \). Alternatively, we can say that, by taking convolution with the filter \( A(k, k') \), \( S(k, p) \) makes contribution to only a few frequency neighbors of \( Y(k, p) \). As for dereverberation, we can apply deconvolution or inverse filtering to \( \{Y(k', p')|k' \in [k - l, k + l]\} \) to recover \( S(k, p) \), and perfect dereverberation performance can be expected as long as the inverse filters are accurate.

However it is very difficult to estimate the inverse filters in practice. In this work, we use deep neural network to perform supervised subband inverse filtering. Basically, the network takes as input the subband reverberant speech, and outputs its corresponding desired signal. All frequencies/subbands are independently processed using the same network. We remind that the desired signal is \( x(n) \) presented in Eq. (2), obtained by \( x(n) = s(n) \ast a(n) = s(n) \ast (a(n)w(n)) \). The STFT of \( x(n) \) is denoted as \( X(k, p) \).

Formally, for frequency \( k \), the network input is a sequence of subband reverberant speech:

\[
Y(k) = [y(k, 1), \ldots, y(k, p), \ldots, y(k, P)]
\]

where \( y(k, p) \) is a vector composed of the real (\( \text{Re} \{ \} \)) and imaginary (\( \text{Im} \{ \} \)) parts of the STFT coefficient for frequencies from \( k - L \) to \( k + L \):

\[
y(k, p) = [\text{Re}\{Y(k - L, p)\}, \text{Im}\{Y(k - L, p)\}, \ldots, \text{Re}\{Y(k + L, p)\}, \text{Im}\{Y(k + L, p)\}]^T \in \mathbb{R}^{2(2L + 1) \times 1}
\]

The number of neighbour frequencies, i.e. \( L \), is normally set to be larger than \( L \), since we would like to predict the target signal for frequency \( k \) by learning not only inverse filtering, but also the spectral pattern of speech within a wider frequency band. The target sequence is the magnitude spectrum of frequency \( k \) of the desired signal:

\[
X(k) = [|X(k, 1)|, \ldots, |X(k, p)|, \ldots, |X(k, P)|]
\]

To make the network training more stable, we normalize the input sequence to the same level, by dividing the average magnitude of the \( k \)-th frequency, i.e. \( \frac{1}{P} \sum_{p=1}^{P} |Y(k, p)| \). Correspondingly, the target sequence is also normalized with this factor. Then the dynamic range of target sequence is further compressed by taking its cubic root.

At inference, the predicted magnitude (after taking its cube and inverse normalization) is combined with the phase of input speech, and then inverse STFT is applied to obtained the time domain enhanced signal, denoted as \( \hat{x}(n) \).

### 3.1. Experimental Setup

The REVERB challenge dataset [27] is used for training and evaluating our proposed method. Clean speech signals for this dataset come from the WSJCAM0 and MC-WSJ-AV corpora. The reverberation time \( T_{60} \) for three experimental rooms, i.e. small room, medium room and large room, are 0.25 s, 0.5 s and 0.7 s, respectively. The distances between speaker and microphone array are set to either 50 cm (near) or 200 cm (far). Speech signals are added with 20 dB of air-conditioning noise. The REVERB challenge is a multi-channel dataset, but we only use the first channel for our experiments. Data is split for training, validation and test following the REVERB challenge principle. The amount of training data is about 16 hours.

The sampling rate is 16 kHz. We apply a 512-point STFT using a Hamming window with a 256-point frame shift. The number of neighbour frequencies is set to \( L = 15 \). For training, the signal length is set to a constant value of \( P = 500 \). The test signals with variant length are directly fed into the network for inference. The subband training samples are shuffled within a batch. The number of hidden units of LSTM layers are set to 256 for each direction. The total number of model parameters is about 2.2 M. The code and audio examples of this paper are available on our website [4].

### 3.2. Comparison with Other Dereverberation Methods

The evaluation metrics used in the REVERB challenge are taken in this work, including cepstrum distance (CD) [28], speech to reverberation modulation energy ratio (SMR) [29], Frequency Weighted Segmental SNR (fwsSNRseg), and Perceptual evaluation of speech quality (PESQ) [30]. We compare the dereverberation capability of the proposed subband network with other single-channel dereverberation methods, including (i) WPE [11]; (ii) DNN proposed in [31]; (iii) Wide Residual Network (WRN) proposed in [22]; (iv) the method of TCN with self-attention (TCN-SA) proposed in [21]. The performance scores of these methods are directly quoted from their original papers.

For fair comparison, in this experiment the proposed method takes the direct-path signal as learning target, as done by other deep-learning based methods. Table 1 shows the results. It can be seen that the proposed subband network achieves very competitive dereverberation performance in terms of CD, fwsSNRseg and PESQ. By focusing on learning the subband convolution/deconvolution and the local spectral pattern, the proposed method can use a small and simple network to learn rich information regarding subband reverberation/dereverberation.

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[1] https://audio.westlake.edu.cn/Research/rts.htm
The learning target for deep-learning-based method are all the direct path signal.

| Target   | T_{\text{RIR}}[s] | PESQ↑ | MSE↓ |
|----------|-------------------|------|------|
| direct-path | 0.25              | 1.36 | 2.26 |
|           | 0.5              | 1.29 | 2.49 |
|           | 0.7              | 1.28 | 2.32 |
| early     | 0.25              | 2.48 | 3.69 |
|           | 0.5              | 1.49 | 2.72 |
|           | 0.7              | 1.45 | 2.63 |
| RTS0.1   | 0.25              | 2.31 | 3.85 |
|           | 0.5              | 1.37 | 2.76 |
|           | 0.7              | 1.34 | 2.57 |
| RTS0.15  | 0.25              | 2.63 | 3.86 |
|           | 0.5              | 1.50 | 2.96 |
|           | 0.7              | 1.42 | 2.71 |
| RTS0.2   | 0.25              | 2.86 | 3.95 |
|           | 0.5              | 1.69 | 3.17 |
|           | 0.7              | 1.54 | 2.89 |

3.3. Evaluation of Reverberation Time Shortening Target

We evaluate the effectiveness of the proposed RTS target. We fix the target T_{\text{RIR}} for all utterances with different original T_{\text{RIR}}. Three target T_{\text{RIR}}s are tested: 0.1 s, 0.15 s and 0.2 s, which are referred to as RTS0.1, RTS0.15 and RTS0.2 respectively. We compare the proposed target with two other targets: (i) direct-path and (ii) direct-path plus 50 ms of early reflections, simply referred to as early. In this experiment, we use PESQ as the performance metric, which takes the respective target signal as the reference signal for different methods. In addition, we also evaluate the prediction error (MSE) between the predicted and target magnitude spectra, which reflects how well the network can solve the given problem.

In order to further evaluate the effect of the proposed training target, we analyze the remaining RIR of the enhanced speech \( \hat{x}(n) \), which is approximately identified as

\[
\hat{a}(n) = \text{Re} \left\{ \text{IDFT} \left[ \text{DFT}(\hat{x}(n)) \right] \text{DFT}(s(n)) \right\}
\]

where DFT and IDFT denote discrete Fourier transform and inverse DFT, respectively. Then the Energy Decay Curve (EDC) can be obtained based on the Schroeder integral [33]:

\[
\text{EDC}(n) = \sum_{n'=n}^{N} \hat{a}^2(n')
\]

3.4. Energy Decay Curve

The long tail includes both remaining late reverberation and prediction errors. By listening to the enhanced signals, the amount of remaining early reflections can be correctly reflected by EDCs, while the long tail of EDCs are more related to the amount of signal distortions and unnaturalness. For the proposed training target, increasing the target T_{\text{RIR}} from 0.1 s to 0.2 s, EDC becomes higher at the early stage (corresponding to more remaining early reflections), and lower at the late stage (corresponding to less prediction errors). Compared to early, the proposed targets has a lower EDC at the very early stage (earlier than 30 ms), and a much lower EDC tail. Overall, to relax the direct-path requirement and have less signal distortions, the proposed target is a better choice than early.

4. Conclusion

In this paper we have proposed a subband dereverberation network, and also a new learning target, called reverberation time shortening (RTS). The subband network, can be seen as a subband inverse filtering network, achieves outstanding dereverberation performance. The RTS target suppresses reverberation
and meanwhile maintain the exponential decaying property of reverberation. The exponential decaying property maintains the sound naturalness and also eases the network training. As a result, the prediction error and signal distortions are reduced.

5. References

[1] K. S. Helfer and L. A. Wilber, “Hearing loss, aging, and speech perception in reverberation and noise,” *J. Speech Hearing Res.*, vol. 33, p. 149–155, 1990.

[2] T. Yoshikawa, A. Sehr, M. Delcroix, K. Kinoshita, R. Maas, T. Nakatani, and W. Kellermann, “Making machines understand us in reverberant rooms: Robustness against reverberation for automatic speech recognition,” *IEEE Signal Processing Magazine*, vol. 29, no. 6, pp. 114–126, 2012.

[3] I. Arweiler and J. M. Buchholz, “The influence of spectral characteristics of early reflections on speech intelligibility,” *J. Acoust. Soc. Amer.*, vol. 130, no. 2, p. 996–1005, 2011.

[4] X. Li, L. Girin, S. Gannot, and R. Horaud, “Multichannel online dereverberation based on spectral magnitude inverse filtering,” *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 27, no. 9, pp. 1365–1377, 2019.

[5] X. Li, S. Gannot, L. Girin, and R. Horaud, “Multichannel identification and nonnegative equalization for dereverberation and noise reduction based on convolutive transfer function,” *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 26, no. 10, pp. 1755–1768, 2018.

[6] X. Li, S. Gannot, L. Girin, and R. Horaud, “Multisource mint using the convolutive transfer function,” *IEEE International Conference on Acoustic, Speech and Signal Processing*, pp. 756–760, 2018.

[7] A. Swami, G. Giannakis, and S. Shamsunder, “Multichannel arma processes,” *IEEE Transactions on Signal Processing*, vol. 42, no. 4, pp. 898–913, 1994.

[8] S. T. Neely and J. B. Allen, “Invertibility of a room impulse response,” *J. Acoust. Soc. Amer.*, vol. 66, no. 1, p. 165–169, 1979.

[9] M. Miyoshi and Y. Kaneda, “Inverse filtering of room acoustics,” *IEEE Transactions on acoustics, speech, and signal processing*, vol. 36, no. 2, p. 145–152, 1988.

[10] T. Nakatani, T. Yoshikawa, K. Kinoshita, M. Miyoshi, and B.-H. Juang, “Speech dereverberation based on variance-normalized delayed linear prediction,” *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 18, no. 7, pp. 1717–1731, 2010.

[11] M. Delcroix, T. Yoshikawa, A. Ogawa, Y. Kubo, M. Fujimoto, N. Ito, K. Kinoshita, M. Espli, T. Horii, T. Nakatani, and A. Nakamura, “Linear prediction-based dereverberation with advanced speech enhancement and recognition technologies for the reverb challenge,” *REVERB Workshop*, 2014.

[12] A. Habets, S. Gannot, and I. Cohen, “Late reverberant spectral variance estimation based on a statistical model,” *IEEE Signal Processing Letters*, vol. 16, no. 9, p. 770773, 2000.

[13] M. Unoki, M. Furukawa, K. Sakata, and M. Akagi, “A method based on the rtf concept for dereverberating the power envelope from the reverberant signal,” *IEEE International Conference on Acoustic, Speech and Signal Processing*, pp. I–I, 2003.

[14] S. Braun, A. Kuklakisfis, O. Schwartz, O. Thiergart, E. A. Habets, S. Gannot, S. Doclo, and J. Jensen, “Evaluation and comparison of late reverberation power spectral density estimators,” *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 26, no. 6, pp. 1056–1071, 2018.

[15] K. Han, Y. Wang, and D. Wang, “Learning spectral mapping for speech dereverberation,” *IEEE International Conference on Acoustic, Speech and Signal Processing*, pp. 4628–4632, 2014.

[16] K. Han, Y. Wang, D. Wang, W. S. Woods, I. Merks, and T. Zhang, “Learning spectral mapping for speech dereverberation and denoising,” *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 23, no. 6, pp. 982–992, 2015.

[17] Y. Zhao, D. Wang, B. Xu, and T. Zhang, “Late reverberation suppression using recurrent neural networks with long short-term memory,” *IEEE International Conference on Acoustic, Speech and Signal Processing*, pp. 5434–5438, 2018.

[18] J. F. Santos and T. H. Falk, “Speech dereverberation with context-aware recurrent neural networks,” *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 26, no. 7, pp. 1236–1246, 2018.

[19] C. Chun, K. M. Jeon, C. Leem, B. Lee, and W. Choi, “Comparison of cnn-based speech dereverberation using neural vocoder,” *International Conference on Artificial Intelligence in Information and Communication*, pp. 251–254, 2021.

[20] Z. Wang and D. Wang, “Deep learning based target cancellation for speech dereverberation,” *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 28, pp. 941–950, 2020.

[21] Y. Zhao, D. Wang, B. Xu, and T. Zhang, “Monaural speech dereverberation using temporal convolutional networks with self attention,” *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 28, pp. 1598–1607, 2020.

[22] Y. Zhao and D. Wang, “Noisy-reverberant speech enhancement using densenet with time-frequency attention,” *Proc. Interspeech*, pp. 3261–3265, 2020.

[23] H. Wang, B. Wu, L. Chen, M. Yu, J. Yu, Y. Xu, S. X. Zhang, C. Weng, D. Su, and D. Yu, “Tecanet: Temporal-contextual attention network for environment-aware speech dereverberation,” *Proc. Interspeech*, pp. 1109–1113, 2021.

[24] X. Li and H. Radu, “Online monaural speech enhancement using delayed subband lstm,” *Proc. Interspeech*, pp. 2462–2466, 2020.

[25] X. Li and R. Horaud, “Narrow-band deep filtering for multichannel speech enhancement,” arXiv preprint arXiv:1911.10791, 2019.

[26] P. A. Naylör and N. D. Gaubitch, “Speech dereverberation,” *Springer Science & Business Media*, 2010.

[27] K. Kinoshita, M. Delcroix, S. Gannot, E. A. P. Habets, R. Haeb-Umbach, W. Kellermann, V. Leutnant, R. Maas, T. Nakatani, B. Raj, A. Sehr, and T. Yoshikawa, “A summary of the reverb challenge: State-of-the-art and remaining challenges in reverberant speech processing research,” *EURASIP J. Adv. Signal Process.*, vol. 2016, no. 1, p. 1–19, 2016.

[28] J. Ma, Y. Hu, and P. C. Loizou, “Objective measures for predicting speech intelligibility in noisy conditions based on new band-importance functions,” *J. Acoust. Soc. Amer.*, vol. 125, p. 3387–3405, 2009.

[29] T. H. Falk, C. Zheng, and W. Chan, “A non-intrusive quality and intelligibility measure of reverberant and dereverberated speech,” *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 18, no. 7, p. 1766–1774, Sep. 2010.

[30] A. W. Rix, J. G. Beerends, M. P. Hollier, and A. P. Hekstra, “Perceptual evaluation of speech quality (pesq)-a new method for speech quality assessment of telephone networks and codecs,” *IEEE International Conference on Acoustic, Speech and Signal Processing*, p. 749–752, 2001.

[31] X. Xiao, S. Zhao, D. H. H. Nguyen, X. Zhong, D. L. Jones, E. S. Chng, and H. Li, “Speech dereverberation for enhancement and recognition using dynamic features constrained deep neural networks and feature adaptation,” *EURASIP J. Adv. Signal Process.*, vol. 2016, no. 4, 2016.

[32] A. M. Ribas, J. Llombart and L. Vicente, “Deep speech enhancement using denseunet with time-frequency attention,” arXiv preprint arXiv:1911.10791, 2019.

[33] H. Kuttruff, *room acoustics, 4 edn*. Taylor & Francis, 2000.