MVNET: MEMORY ASSISTANCE AND VOCAL REINFORCEMENT NETWORK FOR SPEECH ENHANCEMENT

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ABSTRACT

Speech enhancement improves speech quality and promotes the performance of various downstream tasks. However, most current speech enhancement work was mainly devoted to improving the performance of downstream automatic speech recognition (ASR), only a relatively small amount of work focused on the automatic speaker verification (ASV) task. In this work, we propose a MVNet consisted of a memory assistance module which improves the performance of downstream ASR and a vocal reinforcement module which boosts the performance of ASV. In addition, we design a new loss function to improve speaker vocal similarity. Experimental results on the Libri2mix dataset show that our method outperforms baseline methods in several metrics, including speech quality, intelligibility, and speaker vocal similarity *et al*.

Index Terms— Speech enhancement, Complex network, Speaker similarity, Memory assistance, Vocal reinforcement

1. INTRODUCTION

The interference of additive noise with speech can seriously reduce the perceptual quality and intelligibility of speech, which increases the difficulty and complexity of speechrelated recognition tasks. In some scenarios, the security of algorithms for tasks such as speech recognition and speaker verification can be seriously threatened by noise interference [1]. Speech enhancement (SE) is an important speech processing task dedicated to improving the perceptual quality as well as the intelligibility of the disturbed speech and to restore the performance of downstream tasks.

A good SE algorithm should obtain the output speech that is closer to the clean speech. And the output speech often has better speech quality and intelligibility than the input speech. In recent years, deep learning methods [2] [3] [4] [5] [6] were widely applied to SE tasks and achieved good results. Deep learning based methods can be classified into time domain and frequency domain depending on how the input speech is processed. The common practice of time domain methods [7] [8] [9] [10] is to map the time domain waveform of noisy speech directly to the time domain waveform of clean speech, through the learned mapping relationship. The frequency domain approach [5] [11] obtains a mask by inputting the noisy speech spectral features into the network. Then the clean speech is obtained by multiplying the mask and the noisy speech.

Most of the previous work focused on improving speech quality as a training goal, and the current mainstream metrics are also based on speech quality. Several studies proposed to train SE models directly with speech quality metrics (PESQ and STOI), including quality-net [12], MetricGAN-u [13] and hifi-gan [14]. These methods achieved a significant improvement in speech quality. However, ASR and ASV pay different attention to speech features. ASR pays more attention to the intelligibility of speech, while ASV pays more attention to speaker vocal similarity. The optimization focus of the two is not consistent. Speech with higher speech quality can have more outstanding performance in the downstream ASR task, while less outstanding in ASV. Current methods greatly improve speech quality (PESQ and STOI), ignoring the importance of vocal information. However, inconsistent vocals will lead to inconsistencies between speakers and increased distortion, which in turn affects the performance of downstream ASVs. We call this the vocal distortion problem.

PFPL [15] started to demonstrate the importance of phonetic information. Their work demonstrates that adding the necessary speech information can guarantee speech details as well as speech quality. This provides us with ideas to alleviate the vocal distortion problem.

In this work, to adapt to both ASR and ASV at the same time, achieve the improvement of speech quality and vocal consistency, we propose a MVNet consisted of a memory assistance module and a vocal feature reinforcement module. Vocal reinforcement module is to extract the vocal information. We consider it important for vocal distortion problem. Memory assistance module is to improve the enhanced performance of the complex network. It reduces the loss from forgetting valid information in long sequences by the network while enhancing the gain from focusing on important information. Besides, we design a similarity joint loss that aims

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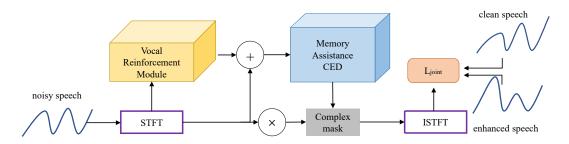


Fig. 1. The overall structure of MVNet.

to alleviate vocal distortion problem. The experiments verify that our method can alleviate the vocal distortion problem while further improving the speech quality.

2. RELATED WORK

2.1. Complex Structure of CRN

The traditional CRN [16] network is symmetric. It uses an encoder-decoder architecture in the time-domain, usually with an LSTM layer in the middle to model the temporal dependencies. The encoder-decoder block consists of convolution and deconvolution layers, batch normalization and activation functions.

To improve the performance of convolution in the complex domain, Tan *et al.* [17] proposed a one encoder two decoders convolution method. Unlike previous CRN that only targets amplitude mapping in the real domain, this network structure is also capable of modeling phase mapping in the complex domain. Compared with the traditional enhancement model, this structure can enhance the amplitude and phase of the speech at the same time, and the enhanced speech no longer needs to reuse the phase of the noisy speech. However, this one encoder two decoders structure actually divided the input into two channels, the real part and the imaginary part, and processed them as real numbers, which did not strictly follow the operation rules of complex numbers.

The above approaches did not directly utilize the prior knowledge of the magnitude and phase correlations of complex arithmetic. Hu *et al.* provided a complex domain convolution model DCCRN [11], which used a complex encoderdecoder combined with a complex LSTM to enhance speech. This network provided the ability to simulate complex multiplication, further enhancing the network's ability to capture the correlation between magnitude and phase. DCCRN has been shown to be effective, and we take it as our baseline model.

2.2. Speech Feature Information

With the research in the signal processing, researchers developed different speech features according to the characteristics of different tasks. Speech feature extraction methods such as MFCC [18] and i-vector [19] showed value in various speech signal processing tasks such as speech recognition, speaker recognition, and phoneme detection. These feature representations focus on different speech information. A suitable feature representation can strongly promote the performance of a specific task.

Hsieh *et al.* [15] proposed a perceptual loss (PFPL) for SE task. They pointed out that phonetic feature information is the key to optimizing human perceptual. PFPL first proposed the idea of adding phonetic feature information to the original speech. This self-supervised SE method is based on DC-CRN and wav2vec [20]. Their experimental results showed effectiveness of phonetic information. And we take PFPL as another baseline model.

3. METHOD

In this work, we propose a MVNet as shown in Fig. 1. In general, we extract the speaker vocal features through vocal reinforcement module, and fuse it with the noisy speech spectrum. A complex mask is then estimated by the memory assistance speech enhancement module and multiplied by the noisy spectrum to obtain the enhanced speech. Besides, we use the proposed similarity joint loss to alleviate vocal distortion problem.

Our method is based on DCCRN which excels in speech quality. We propose the memory assistance module to further improve speech quality and make the model pay more attention to the vocal features. To improve the vocal similarity of speech, we propose the vocal reinforcement module and the similarity joint loss.

3.1. Memory Assistance

In order to make the model further improve the speech quality, and at the same time make it have the ability to pay attention to the vocal features. We propose the memory assistance module under the DCCRN framework, as shown in Fig. 2.

We use 6 complex convolution blocks and symmetric 6 deconvolution blocks to implement the construction of the encoder-decoder with the number of channels set to {32, 64, 128, 256, 256, 256}, where each complex convolution block contains complex Conv2d, complex batch normalization and

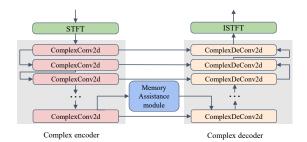


Fig. 2. The memory assistance CED structure.

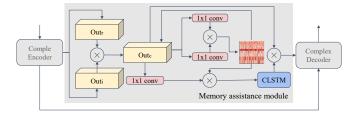


Fig. 3. Memory assistance speech enhancement module. Out_r and Out_i is the real and the imaginary part of the encoder output, respectively. Out_c is the fused complex feature map. CLSTM is the complex LSTM layer.

real-valued PReLU. Each complex Conv2d contains a real conv2d and an imaginary conv2d as in DCCRN [11].

3.1.1. Memory Assistance Module

The overall framework of the DCCRN model is based on CED, and the speech enhancement is mainly realized by the LSTM with causal modeling ability in between. The LSTM network controls the memory state of information in the long-term transmission process through gates, retains important information and forgets the information that the network considers unimportant. It plays the role of information filtering. Vocal information is a very detailed speech feature that can only be noticed from a global perspective. The core logic of the attention mechanism is the global attention, which can capture the vocal features. But only from a global perspective will weaken some local characteristics of speech. Thus, we combine it with the LSTM to form the memory assistance module, which focuses on the both global features and local details of speech.

Placing the attention before LSTM can amplify the memory ability, improves the memory ability of LSTM for global vocal characteristics. If it is placed in the back, LSTM will forgot this information. At this time, the global characteristics of this information will be destroyed, and the global attention will not be able to pay attention to this information. Placing the attention in the back aggravates the forgetting ability. Thus, the final vocal reinforcement is as Fig. 3.

We utilize the features on the crisscross path to achieve global attention through two loops while controlling the mem-

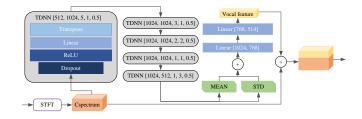


Fig. 4. Vocal reinforcement module.

ory consumption. Module collects contextual information in both horizontal and vertical directions to enhance the expressiveness of feature maps. As shown in Fig. 3, the noisy speech is passed through the complex encoder to obtain the feature maps of both the real and imaginary parts. The feature maps is fused and send into three Conv1ds. The horizontal and vertical attention map is obtained from the first two Conv1ds and then passed back to the input to obtain the global attention map. The global attention map and the output of the third Conv1d are concatenated and fed into the complex LSTM. The output is concatenated with the output of the encoder and fed to the decoder for further processing.

3.2. Vocal Reinforcement

Vocal feature is an important factor affecting the distortion degree of the final enhanced speech. When the vocal features of the enhanced speech and the clean speech are quite different, the speech sounds lack of uniform speaker characteristics, and it does not sound like the original speaker. That causes vocal distortion problem.

The problem of missing vocal characteristics in the process of enhancing speech can be considered from two perspectives. One is that the model does not have the ability to discover such characteristics, and the other is that the optimization direction of the model does not care about this. To improve the vocal similarity of speech from these two perspectives, we propose the vocal reinforcement module and similarity joint loss.

3.2.1. Vocal Reinforcement Module

For the first perspective, our solution is to explicitly add vocal features to the network, which is the direct idea of our vocal reinforcement module.

The way of combining MFCC with TDNN [21] is a common way to obtain speaker representation in ASV, which has a strong expressive ability for vocal features. But MFCC is a compact speech representation. Since it uses mel filter to ignore the dynamics and distribution of speech energy, it still loses some speech details in essence [22]. It is a coarsegrained speech representation. Therefore, we adopt STFT (short-time Fourier transform) to obtain the spectral representation of speech and preserve the temporal information of speech. Combined with TDNN, a fine-grained vocal feature extraction method suitable for speech enhancement is realized. ASV directly uses the speech representation obtained by MFCC and TDNN to do the recognition task. But speech enhancement requires more than just vocal information. We therefore combine the obtained representation as an auxiliary feature with the spectrum obtained by STFT as the input to CED. This forms our vocal reinforcement module.

The proposed vocal reinforcement module is shown in Fig. 4. The spectrum obtained by STFT is sent to 5 TDNNs connected in sequence, the first four output 1024 channels, the last collapses the channels to 512, and the average and standard deviation of the last TDNN's output are calculated and connected to the original output, and then go through two linear layers in turn to get the vector about the vocal features. We fuse the feature vector and the original input into Memory Assistance CED.

3.2.2. Similarity Joint Loss

As mentioned above, to improve the vocal consistency, there are two perspectives. Designing a new loss function is from the second, changing the direction of model optimization.

The complete information of the speech signal is jointly represented by the amplitude and the phase, and the phase contains more detailed information of the speech. In the previous speech enhancement models, SI-SNR [23] was mostly used as the loss function. Although SI-SNR takes into account the vector direction of speech, the calculation process still depends on the signal amplitude. The cosine similarity has a stronger constraint on the consistency of the vector direction. In order to make the model pay more attention to the vector direction, we introduce the cosine similarity to our loss function. The ability of the model to improve the vocal consistency is enhanced by strengthening the constraint of the loss function on the consistency of the vector direction.

The proposed similarity joint loss is to make some improvements on the basis of the loss function of SI-SNR. We take the additive inverse of SI-SNR in our \mathcal{L}_{SI-SNR} , so that larger calculated results indicate less ideal separation. \mathcal{L}_{SI-SNR} is defined as Eq. 1:

$$\begin{cases} \mathbf{s}_{\text{target}} = \frac{\langle \mathbf{s}, \hat{\mathbf{s}} \rangle \mathbf{s}}{\|\mathbf{s}\|^2} \\ \mathbf{e}_{\text{noise}} = \hat{\mathbf{s}} - \mathbf{s}_{\text{target}} \\ \mathcal{L}_{\text{SI-SNR}} = 10 \log_{10} \frac{\|\mathbf{s}_{\text{target}}\|^2}{\|\mathbf{e}_{\text{noise}}\|^2} \end{cases}$$
(1)

where $\langle \cdot, \cdot \rangle$ represents the dot product of two vectors, $\|\cdot\|^2$ is the euclidean norm (L2 norm), s is the clean speech, and \hat{s} means the enhanced speech. SI-SNR is commonly used in papers.

In addition to \mathcal{L}_{SI-SNR} , we propose to use cosine similarity to improve the speaker vocal consistency. The similarity loss is defined as Eq. 2:

$$\mathcal{L}_{\rm smi} = \alpha \log_{10}(1 - \cos_{\rm smi}(\hat{s}, s) + \delta), \tag{2}$$

where the hyperparameter α is the scaling factor, which we set to 100.

The value range of the cosine similarity function $\cos_{smi}(\cdot, \cdot)$ is [-1, 1]. We take the $-\cos_{smi}$, so that the higher the calculation result, the more dissimilar the two speeches are. We add a constant number 1 to fix the range in [0,2]. δ is an extremely small number used to avoid zero values. We smooth the change of the curve through a logarithmic function, so that \mathcal{L}_{smi} has a consistent change trend with \mathcal{L}_{SI-SNR} . Finally, we combine these two functions to propose our similarity joint loss \mathcal{L}_{joint} , defined as Eq. 3:

$$\mathcal{L}_{\text{joint}} = \mathcal{L}_{\text{SI-SNR}} + \mathcal{L}_{\text{smi}}.$$
 (3)

3.3. Training Target

Our training target is to obtain a complex ratio mask(CRM) [24] to estimate clean speech. We adopt the method of signal estimation, that is, the noisy signal and the estimated mask are directly multiplied to obtain the enhanced signal. We improve the performance of the model by minimizing the \mathcal{L}_{joint} between the enhanced and the clean speech.

4. EXPERIMENT AND RESULT

4.1. Setup

4.1.1. Dataset

In our experiments, we use the Librispeech [25] as the clean data, which has 1252 speakers, each speaking for about 25 minutes, for a total of 478 hours of speech duration. The noise data in the experiment comes from the noise dataset WHAM! [26], which consists of real ambient noises.

We mix the Lirispeech and WHAM! datasets in the same way as the LibriMix [27], resulting in a training set with 921 speakers for a total of 364 hours, and a validation set and a test set with 40 speakers for a total of 5.4 hours. The dataset SNR we get from the mix is between -15bB and 5dB.

4.1.2. Evaluation Metrics

The evaluation of our experiments is based on several general metrics of speech quality, including Perceptual Evaluation of Speech Quality (PESQ) [28], Short-Time Objective Intelligibility (STOI) [29], the predicted Mean Opinion Score of signal distortion (CSIG) [30], background noise distortion (CBAK) [30], overall quality (COVL) [30], the scale-invariant signal-to-noise ratio improvement (SI-SNRi) [31], segmental SNR (segSNR) [32] and SIMI (a measure of vocal similarity). SIMI is the proposed new metric to measure the degree of vocal distortion, which is calculated by the speaker recognition algorithm provided by Deep-speaker [33]. The higher the score, the higher the probability that the speaker will be judged to be the same in the ASV task.

4.1.3. Setup and Baseline

We sample waveforms at 16kHz, and set the window length and number of hops to 25 ms and 6.25 ms, respectively. The FFT length is 512. We use Adam optimizer. The initial learning rate is set to 0.001, and when the validation loss increases, the learning rate decreases by 0.5. We train for 200 epochs and record the top PESQ ranked model parameters as our best model for related experiments. For fairness, we run the official codes of baseline models (PFPL and DCCRN) with the same training configuration as ours for comparison.

4.2. Ablation Study for Memory Assistance

We propose the memory assistance module to further improve speech quality and make the model pay more attention to the vocal features.

Table 1. Ablation study for memory assistance. $Ours_{ma}$ and $Ours_{bma}$ represents the result of placing the memory assistance module before the LSTM layer and after the LSTM, respectively. DCCRN represents the results obtained without memory assistance.

Metric	noisy	Ours _{bma}	DCCRN	Ours _{ma}
PESQ	1.18	2.52	2.65	2.70
STOI	0.54	0.81	0.84	0.87
SIMI	0.36	0.39	0.43	0.46

From Table 1, it can be seen that memory assistance module has the best results when placed before LSTM. Memory assistance module can amplify the importance of effective information before the LSTM forgets some information, so that LSTM continues to amplify those effective information. When the memory assistance module is placed behind LSTM, the degree of forgetting of the LSTM will be aggravated, thereby reducing the performance of the model.

Memory assistance module outperforms DCCRN in PESQ, STOI and SIMI. This indicates its ability to further improve speech quality while empowering the model to focus on vocal features.

4.3. Ablation Study for Vocal Reinforcement

To improve the vocal similarity of speech, we propose the vocal reinforcement module and the similarity joint loss. We compare with PFPL(with phonetic information) and DC-CRN(without any speech information). Results are shown in Table 2, our results are significantly better than the above methods.

PFPL explicitly added the additional information (phonetic information) to the DCCRN. This additional information contained more speech details, which made the PESQ, SIMI and CSIG of PFPL higher than those of DCCRN. However, PFPL did not modify the original CED structure of DCCRN, and its model did not have the ability to adapt to

Table 2. Ablation study for vocal reinforcement. $Ours_{vr}$ is the model with only the vocal reinforcement. $Ours_{MVL}$ is the MVNet with both memory assistance and vocal reinforcement

-	Metric	noisy	DCCRN	PFPL	Ours _{vr}	Ours _{MVL}
	PESQ	1.18	2.65	2.71	2.90	2.88
	STOI	0.54	0.84	0.78	0.91	0.91
	SIMI	0.36	0.43	0.51	0.52	0.52
	SegSNR	2.07	6.49	5.58	5.88	6.55
	CSIG	2.02	2.10	2.37	2.47	2.44
	SI-SNR _i	-	6.98	6.27	9.88	9.97

this fine-grained information. Thus, its STOI, SegSNR and SI-SNR_i were degraded. Compared with DCCRN and PFPL, both $Ours_{vr}$ and $Ours_{MVL}$ have better SIMI and CSIG scores, which prove that the vocal reinforcement can improve the vocal consistency. Since $Ours_{vr}$ lacks the memory assistance module in $Ours_{MVL}$, the local details (SegSNR) and overall performance (SI-SNR_i) of $Ours_{vr}$ are worse than $Ours_{MVL}$.

4.4. Comprehensive Evaluation

We comprehensively evaluate the performance of our method on various metrics, as shown in Table 3. Our model outperforms the baseline models in all metrics and lower distortion can be guaranteed while maintaining higher speech quality.

5. CONCLUSION

In this work, we propose the MVNet consisted of a memory assistance module and a vocal reinforcement module. Memory assistance module is proposed to further improve the speech quality while making the model focus more on vocal features. Vocal reinforcement module explicitly introduces vocal features to improve the speaker vocal similarity. Besides, we design a similarity joint loss, which aims to improve the speaker vocal consistency. Experiments verify that the MVNet can further improve speech quality while maintaining the increase in speaker similarity and the decrease in speech distortion, which correspond to the concerns of the ASR and ASV tasks, respectively. In the future, we will continue to explore what affects speech enhancement performance.

6. REFERENCES

- Guangke Chen, Sen Chenb, Lingling Fan, Xiaoning Du, Zhe Zhao, Fu Song, and Yang Liu, "Who is real bob? adversarial attacks on speaker recognition systems," in 2021 IEEE Symposium on Security and Privacy (SP). IEEE, 2021, pp. 694–711.
- [2] Andong Li, Wenzhe Liu, Chengshi Zheng, Cunhang Fan, and Xiaodong Li, "Two heads are better than one: A two-stage complex spectral mapping approach

Table 5. Completensive evaluation.							
PESQ	STOI	CSIG	CBAK	CVOL	SIMI	SegSNR	SI-SNR _i
1.18	0.54	2.02	1.99	1.75	0.36	2.07	-
2.65	0.84	2.10	2.11	1.91	0.43	6.49	9.04
2.71	0.78	2.37	2.45	2.12	0.51	5.58	8.34
2.70	0.87	2.26	2.34	2.08	0.46	6.37	10.61
2.90	0.91	2.47	2.60	2.61	0.52	5.88	11.94
2.88	0.91	2.44	2.59	2.27	0.52	6.55	12.04
	1.18 2.65 2.71 2.70 2.90	PESQ STOI 1.18 0.54 2.65 0.84 2.71 0.78 2.70 0.87 2.90 0.91	PESQSTOICSIG1.180.542.022.650.842.102.710.782.372.700.872.262.900.912.47	PESQSTOICSIGCBAK1.180.542.021.992.650.842.102.112.710.782.372.452.700.872.262.342.900.912.472.60	PESQSTOICSIGCBAKCVOL1.180.542.021.991.752.650.842.102.111.912.710.782.372.452.122.700.872.262.342.082.900.912.472.602.61	PESQSTOICSIGCBAKCVOLSIMI1.180.542.021.991.750.362.650.842.102.111.910.432.710.782.372.452.120.512.700.872.262.342.080.462.900.912.472.602.610.52	PESQ STOI CSIG CBAK CVOL SIMI SegSNR 1.18 0.54 2.02 1.99 1.75 0.36 2.07 2.65 0.84 2.10 2.11 1.91 0.43 6.49 2.71 0.78 2.37 2.45 2.12 0.51 5.58 2.70 0.87 2.26 2.34 2.08 0.46 6.37 2.90 0.91 2.47 2.60 2.61 0.52 5.88

Table 3. Comprehensive evaluation

for monaural speech enhancement," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 29, pp. 1829–1843, 2021.

- [3] Sujan Kumar Roy, Aaron Nicolson, and Kuldip K. Paliwal, "Deeplpc: A deep learning approach to augmented kalman filter-based single-channel speech enhancement," *IEEE Access*, vol. 9, pp. 64524–64538, 2021.
- [4] Ke Tan and DeLiang Wang, "Towards model compression for deep learning based speech enhancement," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 29, pp. 1785–1794, 2021.
- [5] Xiang Hao, Xiangdong Su, Radu Horaud, and Xiaofei Li, "Fullsubnet: a full-band and sub-band fusion model for real-time single-channel speech enhancement," in *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).* IEEE, 2021, pp. 6633–6637.
- [6] A Karthik and JL MazherIqbal, "Efficient speech enhancement using recurrent convolution encoder and decoder," *Wireless Personal Communications*, vol. 119, no. 3, pp. 1959–1973, 2021.
- [7] Ashutosh Pandey and DeLiang Wang, "Densely connected neural network with dilated convolutions for real-time speech enhancement in the time domain," in *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).* IEEE, 2020, pp. 6629–6633.
- [8] Jingjing Chen, Qirong Mao, and Dong Liu, "Dualpath transformer network: Direct context-aware modeling for end-to-end monaural speech separation," *arXiv* preprint arXiv:2007.13975, 2020.
- [9] Yi Luo, Zhuo Chen, and Takuya Yoshioka, "Dualpath rnn: efficient long sequence modeling for timedomain single-channel speech separation," in *ICASSP* 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 46–50.

- [10] Kai Wang, Bengbeng He, and Wei-Ping Zhu, "Tstnn: Two-stage transformer based neural network for speech enhancement in the time domain," in *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).* IEEE, 2021, pp. 7098–7102.
- [11] Yanxin Hu, Yun Liu, Shubo Lv, Mengtao Xing, Shimin Zhang, Yihui Fu, Jian Wu, Bihong Zhang, and Lei Xie, "Dccrn: Deep complex convolution recurrent network for phase-aware speech enhancement," *arXiv preprint arXiv:2008.00264*, 2020.
- [12] Szu-Wei Fu, Chien-Feng Liao, and Yu Tsao, "Learning with learned loss function: Speech enhancement with quality-net to improve perceptual evaluation of speech quality," *IEEE Signal Processing Letters*, vol. 27, pp. 26–30, 2019.
- [13] Szu-Wei Fu, Cheng Yu, Kuo-Hsuan Hung, Mirco Ravanelli, and Yu Tsao, "Metricgan-u: Unsupervised speech enhancement/dereverberation based only on noisy/reverberated speech," in *ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).* IEEE, 2022, pp. 7412–7416.
- [14] Jungil Kong, Jaehyeon Kim, and Jaekyoung Bae, "Hifigan: Generative adversarial networks for efficient and high fidelity speech synthesis," *Advances in Neural Information Processing Systems*, vol. 33, pp. 17022– 17033, 2020.
- [15] Tsun-An Hsieh, Cheng Yu, Szu-Wei Fu, Xugang Lu, and Yu Tsao, "Improving perceptual quality by phone-fortified perceptual loss using wasserstein distance for speech enhancement," *arXiv preprint arXiv:2010.15174*, 2020.
- [16] Ke Tan and DeLiang Wang, "A convolutional recurrent neural network for real-time speech enhancement.," in *Interspeech*, 2018, vol. 2018, pp. 3229–3233.
- [17] Ke Tan and DeLiang Wang, "Complex spectral mapping with a convolutional recurrent network for monaural speech enhancement," in *ICASSP 2019-2019 IEEE*

International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 6865–6869.

- [18] Vibha Tiwari, "Mfcc and its applications in speaker recognition," *International journal on emerging technologies*, vol. 1, no. 1, pp. 19–22, 2010.
- [19] Daniel Garcia-Romero and Carol Y Espy-Wilson, "Analysis of i-vector length normalization in speaker recognition systems," in *Twelfth annual conference* of the international speech communication association, 2011.
- [20] Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli, "wav2vec 2.0: A framework for self-supervised learning of speech representations," *Advances in Neural Information Processing Systems*, vol. 33, pp. 12449–12460, 2020.
- [21] Wu Ji and Keong Chan Chee, "Prediction of hourly solar radiation using a novel hybrid model of arma and tdnn," *Solar Energy*, vol. 85, no. 5, pp. 808–817, 2011.
- [22] Farnood Faraji, Yazid Attabi, Benoit Champagne, and Wei-Ping Zhu, "On the use of audio fingerprinting features for speech enhancement with generative adversarial network," in 2020 IEEE Workshop on Signal Processing Systems (SiPS), 2020, pp. 1–6.
- [23] Yi Luo and Nima Mesgarani, "Conv-tasnet: Surpassing ideal time–frequency magnitude masking for speech separation," *IEEE/ACM transactions on audio, speech, and language processing*, vol. 27, no. 8, pp. 1256–1266, 2019.
- [24] Donald S Williamson, Yuxuan Wang, and DeLiang Wang, "Complex ratio masking for monaural speech separation," *IEEE/ACM transactions on audio, speech, and language processing*, vol. 24, no. 3, pp. 483–492, 2015.
- [25] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur, "Librispeech: an asr corpus based on public domain audio books," in 2015 IEEE international conference on acoustics, speech and signal processing (ICASSP). IEEE, 2015, pp. 5206–5210.
- [26] Gordon Wichern, Joe Antognini, Michael Flynn, Licheng Richard Zhu, Emmett McQuinn, Dwight Crow, Ethan Manilow, and Jonathan Le Roux, "Wham!: Extending speech separation to noisy environments," arXiv preprint arXiv:1907.01160, 2019.
- [27] Joris Cosentino, Manuel Pariente, Samuele Cornell, Antoine Deleforge, and Emmanuel Vincent, "Librimix: An open-source dataset for generalizable speech separation," *arXiv preprint arXiv:2005.11262*, 2020.

- [28] Antony W Rix, John G Beerends, Michael P Hollier, and Andries P Hekstra, "Perceptual evaluation of speech quality (pesq)-a new method for speech quality assessment of telephone networks and codecs," in 2001 IEEE international conference on acoustics, speech, and signal processing. Proceedings (Cat. No. 01CH37221). IEEE, 2001, vol. 2, pp. 749–752.
- [29] Cees H Taal, Richard C Hendriks, Richard Heusdens, and Jesper Jensen, "An algorithm for intelligibility prediction of time-frequency weighted noisy speech," *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 19, no. 7, pp. 2125–2136, 2011.
- [30] Yi Hu and Philipos C Loizou, "Evaluation of objective quality measures for speech enhancement," *IEEE Transactions on audio, speech, and language processing*, vol. 16, no. 1, pp. 229–238, 2007.
- [31] Emmanuel Vincent, Rémi Gribonval, and Cédric Févotte, "Performance measurement in blind audio source separation," *IEEE transactions on audio, speech, and language processing*, vol. 14, no. 4, pp. 1462–1469, 2006.
- [32] Schuyler R Quackenbush, "Objective measures of speech quality (subjective)," 1986.
- [33] Chao Li, Xiaokong Ma, Bing Jiang, Xiangang Li, Xuewei Zhang, Xiao Liu, Ying Cao, Ajay Kannan, and Zhenyao Zhu, "Deep speaker: an end-to-end neural speaker embedding system," arXiv preprint arXiv:1705.02304, 2017.