METRIC-ORIENTED SPEECH ENHANCEMENT USING DIFFUSION PROBABILISTIC MODEL

Chen Chen, Yuchen Hu, Weiwei Weng, Eng Siong Chng

School of Computer Science and Engineering, Nanyang Technological University, Singapore
CHEN1436@e.ntu.edu.sg

ABSTRACT

Deep neural network based speech enhancement technique focuses on learning a noisy-to-clean transformation supervised by paired training data. However, the task-specific evaluation metric (e.g., PESQ) is usually non-differentiable and can not be directly constructed in the training criteria. This mismatch between the training objective and evaluation metric likely results in sub-optimal performance. To alleviate it, we propose a metric-oriented speech enhancement method (MOSE), which leverages the recent advances in the diffusion probabilistic model and integrates a metric-oriented training strategy into its reverse process. Specifically, we design an actor-critic based framework that considers the evaluation metric as a posterior reward, thus guiding the reverse process to the metric-increasing direction. The experimental results demonstrate that MOSE obviously benefits from metric-oriented training and surpasses the generative baselines in terms of all evaluation metrics.

Index Terms— Diffusion probabilistic model, speech enhancement, reinforcement learning

1. INTRODUCTION

Recent advances in deep learning has brought remarkable success to the speech enhancement technique, where a noisy-to-clean transformation is learned to remove additive noises by a supervised learning manner [1–4]. However, this paradigm suffers from a mismatch between training and evaluation: the training criterion (e.g., Mean Square Error) must be differentiable for gradient calculation [5], while the evaluation metric (e.g. PESQ) are usually non-differentiable, thus can not be directly modeled in loss function as minimized objective. Consequently, the optimized model after training can not achieve best performance in terms of evaluation metric.

This mismatch is also reported in other supervised learning tasks, such as machine translation [6, 7] and automatic speech recognition [8–10]. Prior works have utilized reinforcement learning (RL) based algorithms to harmonize the mismatch using metric-based training approach [11], as these tasks contain a sequential decoding process that can be naturally viewed as Markov Decision Process (MDP) [12]. Nevertheless, as a regression task, mainstream SE approaches train a one-shot discriminative model without the time-step concept for MDP, which is infeasible for RL-based optimization.

Diffusion probabilistic model [13], showing outstanding results in generative tasks [14, 15], brings possibility for metric-based optimization of SE task, as it inherently consists of MDP-based diffusion and reverse processes [16]. More specifically, an isotropic Gaussian distribution is added to the clean speech during step-by-step diffusion process, and in the reverse process, gradually estimates and subtracts additive noise to restore the clean input [17].

In this work, we present a metric-oriented speech enhancement method called MOSE, which effectively constructs the non-differentiable metric into the training objective. Inspired by actor-critic based algorithm [18], we design a value-based neural network that is updated by Bellman Error [19] to evaluate current policy in terms of metric-related reward function, then it guides the prediction of subtracted noise in a reverse process by the differentiable manner. In this way, the original policy is optimized to the metric-increasing direction, while the value-based network is trained to provide reasonable feedback. Experimental results demonstrate that MOSE obviously benefit from metric-oriented training and beat other generative methods in terms of all metrics. Furthermore, it shows better generalization in face of unseen noises with large domain mismatch.

2. PRELIMINARIES

We first define noisy speech as y and define its corresponding ground-truth clean speech as x_0. The speech enhancement task aims to learn a transformation f that converts the noisy input to clean signal: $x_0 = f(y),\ x_0, y \in \mathbb{R}^L$.

2.1. Diffusion Probabilistic Model

In this part, we briefly introduce the diffusion process and the reverse process of the typical diffusion probabilistic model.

Diffusion process is formulated as a T-step Markov chain that gradually adds Gaussian noise to the clean signal x_0 in each step t. The Gaussian model is denoted as $q(x_t|x_{t-1}) =$

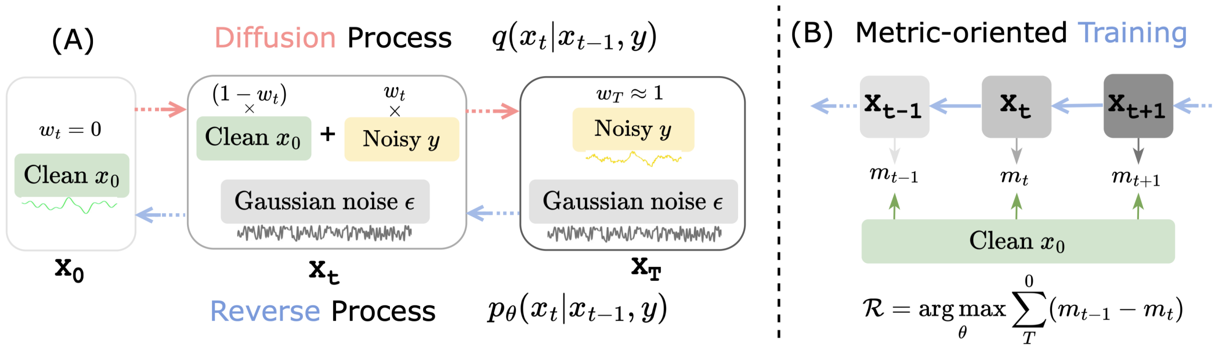

Fig. 1: The conditional diffusion probabilistic model (A) and metric-oriented training (B). The red and blue arrows respectively denotes the diffusion and reverse process. w_t is the weight of linear interpolation, and m_t is the task-specific metric.

$\mathcal{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t I)$, where β_t is a small positive constant that serve as a pre-defined schedule. With enough diffusion step T, the latent variable x_T can be finally converted to an isotropic Gaussian distribution $p_{latent}(x_T) = \mathcal{N}(0, I)$. Therefore, based on x_0, the sampling distribution of each step in the Markov chain can be derived as the following:

$$q(x_t|x_0) = \mathcal{N}(x_t; \sqrt{\bar{\alpha}_t}x_0, (1 - \bar{\alpha}_t)I), \tag{1}$$

where $\alpha_t = 1 - \beta_t$ and $\bar{\alpha}_t = \prod_{s=1}^t \alpha_s$.

Reverse process aims to restore the x_0 from the latent variable x_T along another Markov chain, which is denoted as $p_\theta(x_{t-1}|x_t)$, where θ is learnable parameters. As marginal likelihood $p_\theta(x_0) = \int p_\theta(x_0, \cdots, x_{T-1}|x_T) \cdot p_{\text{latent}}(x_T)dx_{1:T}$ is intractable for calculation, the ELBO [13] is utilized to approximate a learning objective for neural model training. Therefore, the equation of the reverse process can be denoted as:

$$\begin{aligned} &p_\theta(x_{t-1}|x_t) = \mathcal{N}(x_{t-1}; \mu_\theta(x_t, t), \tilde{\beta}_t I), \\ &\text{where} \quad \mu_\theta(x_t, t) = \frac{1}{\sqrt{\alpha_t}}(x_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon_\theta(x_t, t)) \end{aligned} \tag{2}$$

Here $\mu_\theta(x_t, t)$ denotes the mean of x_{t-1}, which is obtained by subtracting the estimated Gaussian noise $\epsilon_\theta(x_t, t)$ in the x_t. Furthermore, the variance is derived to a constant $\tilde{\beta}_t = \frac{1-\bar{\alpha}_{t-1}}{1-\bar{\alpha}_t}\beta_t$.

2.2. Reinforcement Learning

Reinforcement learning (RL) is typically formulated as a Markov Decision Process (MDP) that includes a tuple of trajectories $\langle \mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{T} \rangle$. For each time step t, the agent considers state $s_t \in S$ to generate an action $a_t \in \mathcal{A}$ which interacts with environment. The transition dynamics $\mathcal{T}(s_{t+1}|s_t, a_t)$ is defined as transition probability from current state s_t to next state s_{t+1}, and gain an instant reward $r_t(s_t, a_t)$. The objective of RL is to learn optimal policy to maximize the cumulative reward $\mathcal{R}$ along all time steps.

Since the diffusion probabilistic model formulates speech enhancement task as MDP in section 2.1, the RL algorithm can be integrated in the reverse process to explore optimal policy. More specifically, given the current state x_t, the policy network is supposed to predict a Gaussian noise ϵ_t as the current action. After subtracting the ϵ_t in x_t, the x_{t-1} is obtained as next state, as step number t is decreasing during reverse process. Furthermore, the instant reward r_t is calculated by comparison of x_t and x_{t-1}, which guides the update of parameters θ during model training.

3. METHODOLOGY

In this section, we introduce our proposed MOSE, which integrates the metric-oriented training into the reverse process of a conditional diffusion probabilistic model. The overview of MOSE is shown in Fig. 1.

3.1. Conditional Diffusion Probabilistic Model

As real-world noises usually does not obey the Gaussian distribution, we incorporate noisy speech y into the procedures as a conditioner in this part. Specifically, a dynamic weight $w_t \in [0, 1]$ is employed for linear interpolation from x_0 to x_T. Therefore, as shown in Fig. 1, each latent variable x_t consists of three parts: clean component $(1 - w_t) \times x_0$, noisy component $w_t \times y$, and Gaussian Noise ϵ. Furthermore, the diffusion process in Eq. (1) can be rewritten as:

$$q(x_t|x_0, y) = \mathcal{N}(x_t; (1 - w_t)\sqrt{\bar{\alpha}_t}x_0 + w_t\sqrt{\bar{\alpha}_t}y, \delta_t I), \tag{3}$$

$$\text{where} \quad \delta_t = (1 - \bar{\alpha}_t) - w_t^2\bar{\alpha}_t \tag{4}$$

The conditional reverse process starts from x_T with $w_T = 1$, which is denoted as $\mathcal{N}(x_T, \sqrt{\bar{\alpha}_T}y, \delta_T I)$. Referring to Eq. (2), we denoted the conditional reverse process as:

$$p(x_{t-1}|x_t, y) = \mathcal{N}(x_{t-1}; \mu_\theta(x_t, y, t), \tilde{\delta}_t I), \tag{5}$$

where $\mu_\theta(x_t, y, t)$ is the predicted mean of variance x_{t-1}. It means that the neural model θ considers both variance x_t and noisy conditioner y during its prediction. Therefore, similar to Eq. (2), we define the mean of μ_θ as a linear combination of x_t, y, and ϵ_θ:

$$\mu_\theta(x_t, y, t) = c_{xt}x_t + c_{yt}y - c_{\epsilon t}\epsilon_\theta(x_t, y, t), \tag{6}$$

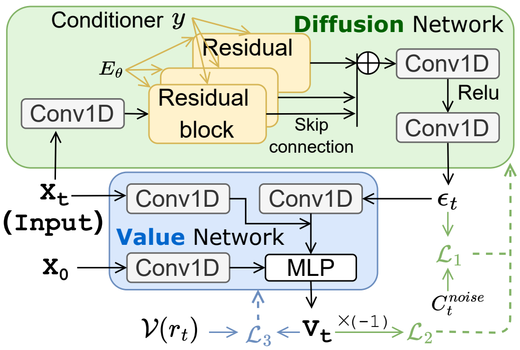

Fig. 2: The main structure of MOSE. Dashed line stands for back propagation for neural network.

where the coefficients c_{xt}, c_{yt}, and $c_{\epsilon t}$ can be derived from the ELBO optimization criterion in [20]. Finally, we combine Gaussian noise ϵ and non-Gaussian noise $y - x_0$ as ground-truth C_t^{noise}:

$$C_t^{noise}(x_0, y, \epsilon) = \frac{m_t\sqrt{\bar{\alpha}_t}}{\sqrt{1-\bar{\alpha}_t}}(y - x_0) + \frac{\sqrt{\delta_t}}{\sqrt{1-\bar{\alpha}_t}}\epsilon \quad (7)$$

$$\nabla_\theta \mathcal{L}_1 = \parallel C_t^{noise}(x_0, y, \epsilon) - \nabla_\theta \epsilon_\theta(x_t, y, t) \parallel_1 \quad (8)$$

where C_t^{noise} provides supervision information, and $\mathcal{L}_1$ is calculated for back propagation of neural network.

3.2. Metric-oriented Training

Given the task-specific evaluation metric m, each t-step variable can calculate the m_t by x_t and x_0 as they are in same shape. In order to directly optimize m_t, an actor-critic RL algorithm is integrated into conditional reverse process, as shown in the Fig. 1 (B).

Since we hope that the latent variable is iterated toward the metric-increasing direction in the reverse process, the reward function is customized as: $r_t = m_{t-1} - m_t$, where t starts from T to 0. However, posterior r_t is obviously non-differentiable for θ, thus failing to propagate gradient. To this end, we further employ a **Value network** V with parameter θ_v as the blue box in Fig. 3, and the original network is denoted as **Diffusion network** D with parameter θ_d for distinction. In general, The Diffusion network consumes x_t to predict the subtracted noise ϵ_t as action, while the Value network generates an score v_t to evaluate this ϵ_t based on x_t. The training strategy of MOSE is explained in Algorithm 1.

MOSE starts training with conventional ELBO optimization, as explained from line 3$\sim$9 in Algorithm 1, only Diffusion network D is trained for N_{th} iterations. Then we present joint training of Diffusion network D and Value network V from lines 10$\sim$18. Minimizing $\mathcal{L}_2 = -V(x_t, \epsilon_t, x_0|\theta_v)$ indicates that D tents to gain higher score from V, and $\mathcal{L}_2$ is simultaneously incorporated with a weight α to stabilize training. In order to encourage Value network V to provide reasonable evaluation, we employ widely used Bellman Error [19] (line 17) to update V, where γ is a decay factor for future reward. Consequently, the output score v_t both considers current and future rewards based on the task-specific metric. For inference, we adopt a fast sampling scheme as same as in [15].

Algorithm 1 MOSE Training

1: Randomly initialize the Diffusion network $D(x|\theta_d)$ and Value network $V(x, \epsilon|\theta_v)$.
2: Initialize N_{total}, N_{th}, γ, and α
3: **for** $i = 1, 2, \cdots, N_{total}$ **do**
4:     Sample (x_0, y) from Dataset
5:     Sample $\epsilon \sim \mathcal{N}(0, I)$ and $t \sim$Uniform$(\{1, \cdots, T\})$
6:     Set $x_t = ((1 - m_t)\sqrt{\bar{\alpha}_t}x_0 + m_t\sqrt{\bar{\alpha}_t}y) + \sqrt{\delta_t}\epsilon$
7:     Calculate C_t^{noise} according to Eq. (7)
8:     **if** $i < N_{th}$ **then**
9:         Update network D by minimizing $\mathcal{L}_1$ in Eq. (8)
10:     **else**
11:         Calculate $\epsilon_t = D(x_t, y, t|\theta_d)$ as action
12:         Calculate $\nabla_{\theta_d}\mathcal{L}_2 = -V(x_t, \nabla_{\theta_d}\epsilon_t, x_0|\theta_v)$
13:         Update D by minimizing $\mathcal{L} = \mathcal{L}_1 + \alpha \cdot \mathcal{L}_2$
14:         Calculate x_{t-1} according to Eq. 6 as next state
15:         Calculate $r_t = m_{t-1}(x_{t-1}, x_0) - m_t(x_{t-1}, x_0)$
16:         Set $\mathcal{V}_t = r_t + \gamma V(x_{t-1}, D(x_{t-1}, y, t-1), x_0|\theta_v)$
17:         Calculate $\nabla_{\theta_v}\mathcal{L}_3 = (\mathcal{V}_t - \nabla_{\theta_v}V(x_t, \epsilon_t, x_0|\theta_v))^2$
18:         Update network V by minimizing $\mathcal{L}_3$
19:     **end if**
20: **end for**

4. EXPERIMENT

4.1. Experimental Setup

Database. We choose the publicly available VoiceBank DEMAND dataset [21] for SE training and evaluation. Specifically, the training set contains 11,572 noisy utterances from 28 speakers and is mixed by 10 different types with four SNR levels (0, 5, 10, and 15 dB) at a sampling rate of 16 kHz, as well as their corresponding clean utterances. The test set contains 5 types of unseen noise in SNR levels (2.5, 7.5, 12.5, and 17.5 dB). To evaluate the performance of a model in unseen noises, we further mix the test set of TIMIT [22] and “helicopter” and “babycry” noises with different SNR levels (-6, -3, 0, 3, 6 dB), where a large domain mismatch exists between training and testing.

Configuration. The internal structure of MOSE is shown in Fig. 3. We employ 30 residual blocks with 64 channels in Diffusion Net. MLP block contains 4 linear layers with ReLU activation function. For training, MOSE takes 50 diffusion steps with training noise schedule $\beta_t \in [1\times10^{-4}, 0.035]$, and the interpolation weight $m_t = \sqrt{(1-\bar{\alpha}_t)/\sqrt{\bar{\alpha}_t}}$. The N_{total}, N_{th}, and γ in Algorithm 1 are respectively set as 40k, 30k, and 0.95. The initial learning rate of Diffusion network is set as 2×10^{-4} for first N_{th} iterations, and decrease to 1×10^{-4}

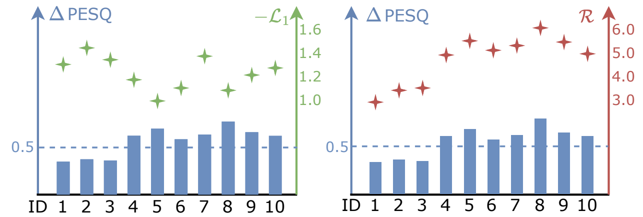

Fig. 3: The relationship between ΔPESQ and training loss $-\mathcal{L}_1$, as well as gained reward $\mathcal{R}$.

Table 1: Result of metric-oriented training.

ID	System	α	PESQ	CSIG	CBAK	COVL
1	Unprocessed	-	1.97	3.35	2.44	2.63
2	MOSE	0	2.44	3.65	2.87	3.01
3	MOSE	0.1	2.48	3.66	2.90	3.06
4		1	**2.54**	**3.73**	**2.93**	**3.12**
5		5	2.51	3.69	2.91	3.08

for $N_{th} \sim N_{total}$ iterations. The learning rate of the Value network is set as 1×10^{-5}. Both networks are optimized by Adam with a batch size of 32. The fast sampling method keeps the same schedule with [20].

Metric. We select the perceptual evaluation of speech quality (PESQ) as the task-specific metric of optimization objective due to its universality. Furthermore, prediction of the signal distortion (CSIG), prediction of the background intrusiveness (CBAK), and prediction of the overall speech quality (COVL) are also reported as references.

4.2. Result and Analysis

4.2.1. Experimental validation of mismatch

We first design an experiment to verify the mismatch problem between the training objective and evaluation metric, and illustrate how we mitigate it. To this end, we train a typical diffusion probabilistic model, where $\mathcal{L}_1$ in Eq (8) is set as the only training objective. Then we sample 10 utterances and add up their $\mathcal{L}_1$ (50 steps), as well as calculate the improvement of PESQ (ΔPESQ). The comparison is visualized in the left part of Fig. 3, and we observe that there is no correlation between $\mathcal{L}_1$ and ΔPESQ, which indicates that SE model trained only by $\mathcal{L}_1$ will lead to sub-optimal performance in terms of PESQ. Meanwhile, we calculate the cumulatively gained reward $\mathcal{R}$ of these utterances after metric-oriented training and visualize in the right of Fig. 3, where an obvious positive correlation can be observed between ΔPESQ and $\mathcal{R}$.

4.2.2. Effect of metric-oriented training

We then examine the effect of proposed metric-oriented training, and the results are reported in Table 1. "Unprocessed" denotes direct evaluation based on noisy data, and α is the weight of $\mathcal{L}_2$ in Algorithm 1. When $\alpha = 0$, SE model are only trained by $\mathcal{L}_1$ loss. We observe that system 3∼5 all surpass system 2 with help of metric-oriented training. When $\alpha = 1$, the SE model achieves the best performance.

Table 2: MOSE *vs.* other methods. "Gen." and "Dis." respectively denote generative and discriminative models.

System	Type	PESQ	CSIG	CBAK	COVL
Unprocessed	-	1.97	3.35	2.44	2.63
DSEGAN [23]	Gen.	2.39	3.46	3.11	2.90
SE-Flow [24]	Gen.	2.28	3.70	3.03	2.97
CDiffuSE [20]	Gen.	2.52	3.72	2.91	3.10
WaveCRN [25]	Dis.	2.64	3.94	**3.37**	3.29
Conv-TasNet [26]	Dis.	**2.67**	**3.94**	3.31	**3.30**
MOSE (ours)	Gen.	2.54	3.72	2.93	3.06

Table 3: PESQ results on TIMIT dataset with different SNRs. "Avg" denotes the average of all SNR levels.

System	Noise level, SNR =					
	-6	-3	0	3	6	Avg.
Noise type: Helicopter						
Unprocessed	1.05	1.07	1.10	1.16	1.26	1.13 +0%
Conv-TasNet [26]	1.06	1.08	1.14	1.21	**1.47**	1.19 +5.3%
MOSE	**1.08**	**1.13**	**1.16**	**1.26**	1.44	**1.21** +7.1%
Noise type: Baby-cry						
Unprocessed	1.06	1.09	1.13	1.18	1.27	1.15 +0%
Conv-TasNet [26]	1.06	1.10	1.15	1.21	1.37	1.18 +2.6%
MOSE	**1.08**	**1.13**	**1.16**	**1.24**	**1.45**	**1.21** +5.2%

In addition, Table 2 summarizes the comparison between MOSE and other competitive SE methods, which contains 3 generative models and 2 discriminative methods. We observe that MOSE surpasses generative baselines in terms of all metrics, however, the best performance is still achieved by discriminative method.

4.2.3. Generalization on unseen noise

We evaluate our trained model in unseen noisy condition with a wide range of SNR levels, where Conv-TasNet method is reproduced for comparison. The PESQ results are shown in Table 3. Despite gaining outstanding performance on the matched test set, we observed that the PESQ of Conv-TasNet dramatically degrades due to noise domain mismatch. However, the MOSE performs better than Conv-TasNet in terms of PESQ, especially in low-SNR conditions.

5. CONCLUSION

In this paper, we propose a speech enhancement method, called MOSE, which addresses the mismatch problem between training objective and evaluation metric. The probabilistic diffusion model is leveraged as MDP based framework, where metric-oriented training is presented in the reverse process. The experimental results demonstrate that MOSE beats other generative baselines in terms of all metrics, and show better generalization on unseen noises.

6. REFERENCES

[1] D. Wang and J. Chen, "Supervised speech separation based on deep learning: An overview," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 26, no. 10, 2018.

[2] Y. Xu, J. Du, L.-R. Dai, and C.-H. Lee, "A regression approach to speech enhancement based on deep neural networks," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 23, no. 1, 2014.

[3] Y. Koizumi, K. Yatabe, M. Delcroix, Y. Masuyama, and D. Takeuchi, "Speech enhancement using self-adaptation and multi-head self-attention," in *ICASSP 2020-2020*, 2020.

[4] C. Chen, N. Hou, D. Ma, and E. S. Chng, "Time domain speech enhancement with attentive multi-scale approach," in *2021 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*. IEEE, 2021, pp. 679–683.

[5] Z. Chen, S. Watanabe, H. Erdogan, and J. R. Hershey, "Speech enhancement and recognition using multi-task learning of long short-term memory recurrent neural networks," in *Conference of the International Speech Communication Association*, 2015.

[6] D. Bahdanau, P. Brakel, K. Xu, A. Goyal, R. Lowe, J. Pineau, A. Courville, and Y. Bengio, "An actor-critic algorithm for squence prediction," 2016.

[7] L. Wu, F. Tian, T. Qin, J. Lai, and T.-Y. Liu, "A study of reinforcement learning for neural machine translation," *arXiv preprint arXiv:1808.08866*, 2018.

[8] R. Prabhavalkar, T. N. Sainath, Y. Wu, P. Nguyen, Z. Chen, C.-C. Chiu, and A. Kannan, "Minimum word error rate training for attention-based sequence-to-sequence models," in *ICASSP*, 2018.

[9] C. Chen, Y. Hu, N. Hou, X. Qi, H. Zou, and E. S. Chng, "Self-critical sequence training for automatic speech recognition," in *ICASSP*, 2022.

[10] C. Chen, Y. Hu, Q. Zhang, H. Zou, B. Zhu, and E. S. Chng, "Leveraging modality-specific representations for audio-visual speech recognition via reinforcement learning," *arXiv preprint arXiv:2212.05301*, 2022.

[11] S. J. Rennie, E. Marcheret, Y. Mroueh, J. Ross, and V. Goel, "Self-critical sequence training for image captioning," in *CVPR*, 2017.

[12] A. Tjandra, S. Sakti, and S. Nakamura, "Sequence-to-sequence asr optimization via reinforcement learning," in *ICASSP*, 2018.

[13] J. Ho, A. Jain, and P. Abbeel, "Denoising diffusion probabilistic models," *Advances in Neural Information Processing Systems*, vol. 33, pp. 6840–6851, 2020.

[14] A. Q. Nichol and P. Dhariwal, "Improved denoising diffusion probabilistic models," in *ICML*, 2021.

[15] Z. Kong, W. Ping, J. Huang, K. Zhao, and B. Catanzaro, "Diffwave: A versatile diffusion model for audio synthesis," *arXiv preprint arXiv:2009.09761*, 2020.

[16] S. Luo and W. Hu, "Diffusion probabilistic models for 3d point cloud generation," in *CVPR*, 2021.

[17] Y.-J. Lu, Y. Tsao, and S. Watanabe, "A study on speech enhancement based on diffusion probabilistic model," in *2021 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, 2021.

[18] C. Chen, H.-Y. Li, X. Zhang, X. Liu, and U.-X. Tan, "Towards robotic picking of targets with background distractors using deep reinforcement learning," in *2019 WRC Symposium on Advanced Robotics and Automation (WRC SARA)*, 2019.

[19] I. Grondman, L. Busoniu, G. A. Lopes, and R. Babuska, "A survey of actor-critic reinforcement learning: Standard and natural policy gradients," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 42, no. 6, 2012.

[20] Y.-J. Lu, Z.-Q. Wang, S. Watanabe, A. Richard, C. Yu, and Y. Tsao, "Conditional diffusion probabilistic model for speech enhancement," in *ICASSP*, 2022.

[21] C. Valentini-Botinhao, X. Wang, S. Takaki, and J. Yamagishi, "Investigating rnn-based speech enhancement methods for noise-robust text-to-speech." in *SSW*, 2016.

[22] J. S. Garofolo, L. F. Lamel, W. M. Fisher, J. G. Fiscus, and D. S. Pallett, "Getting started with the darpa timit cd-rom: An acoustic phonetic continuous speech database," *National Institute of Standards and Technology (NIST), Gaithersburgh, MD*, vol. 107, 1988.

[23] H. Phan, I. V. McLoughlin, L. Pham, O. Y. Chén, P. Koch, M. De Vos, and A. Mertins, "Improving gans for speech enhancement," *IEEE Signal Processing Letters*, 2020.

[24] M. Strauss and B. Edler, "A flow-based neural network for time domain speech enhancement," in *ICASSP*, 2021.

[25] T.-A. Hsieh, H.-M. Wang, X. Lu, and Y. Tsao, "Wavecrn: An efficient convolutional recurrent neural network for end-to-end speech enhancement," *IEEE Signal Processing Letters*, vol. 27, pp. 2149–2153, 2020.

[26] Y. Luo and N. 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.